Project #03 Multimodal Guitar: Performance Toolbox and Study Workbench

Christian Frisson [1,♮], Loïc Reboursière [2,♭], Wen-Yang Chu [1,♯], Otso Lähdeoja [3], John Anderson Mills III [2], Cécile Picard [4], Ao Shen [5], Todor Todoroff [2]

[1] TELE Lab, Catholic University of Louvain (Be); [2] TCTS Lab, Polytechnic Faculty of Mons (Be); [1,2] numediart Research Program on Digital Art Technologies; [3] CICM, University of Paris 8 (Fr); [4] INRIA-REVES Lab, Sophia-Antipolis (Fr); [5] EECE Dept., University of Birmingham (UK)
[♮] Project coordinator; [♭] Performance Toolbox coordinator; [♯] Study Workbench coordinator

***Abstract*—This project aims at studying how recent interactive and interaction technologies would help extend how we play the guitar, thus defining the "*multimodal guitar*". We investigate two axes, 1) "A gestural/polyphonic sensing/processing toolbox to augment guitar performances", and 2) "An interactive guitar score following environment for adaptive learning". These approaches share quite similar technological challenges (sensing, analysis, processing, synthesis and interaction methods) and dissemination intentions (community-based, low-cost, open-source whenever possible), while leading to different applications (respectively artistic and educational), still targeted towards experienced players and beginners.**

We designed and developed a toolbox for multimodal guitar performances containing the following tools: Polyphonic Pitch Estimation (see section III-A1), Fretboard Grouping (see section III-A2), Rear-mounted Pressure Sensors (see section III-B), Infinite Sustain (see section III-C2), Rearranging Looper (see section III-C3), Smart Harmonizer (see section III-C4). The Modal Synthesis tool (see section III-C1) needs be refined before being released.

We designed a low-cost offline system for guitar score following (see section IV-A). An audio modality, polyphonic pitch estimation from a monophonic audio signal, is the main source of the information (see section IV-B), while the visual input modality, finger and headstock tracking using computer vision techniques on two webcams, provides the complementary information (see section IV-C). We built a stable data acquisition approach towards low information loss (see section IV-E). We built a probability-based fusion scheme so as to handle missing data; and unexpected or misinterpreted results from single modalities so as to have better multi-pitch transcription results (see section IV-D). We designed a visual output modality so as to visualize simultaneously the guitar score and feedback from the score following evaluation (see section IV-F). The audio modality and parts of the visual input modality are already designed to run in realtime, we need to improve the multimodal fusion and visualization so that the whole system can run in realtime.

***Index Terms*—Audio- and polyphonic multi-pitch transcription, audio synthesis, digital audio effects, multimodal interaction and gestural sensing, finger tracking, particle filtering, multimodal fusion, guitar score following.**

I. Introduction

A. The guitar, a marker of telecommunications technologies

The evolution of the guitar as a musical instrument has been showcasing several milestones in telecommunication engineering technologies discovered in the last centuries, from vacuum tube amplification, effect pedals with built-in electronic diodes and chips, magnetic/piezoelectric/optical sensing, wireless linking, and so on [20]. The "guitar synthesizer", extending the palette of guitar sounds with synthesis algorithms and effect processing, is composed of a guitar, a monophonic or hexaphonic pickup (the latter allowing signal analysis of individual strings, with magnetic [64] or optical [57, 48] or piezoelectric sensing) and an analog or digital processing device (the latter embedding a microprocessor). However, these processing devices still don't offer today an ergonomic, customizable and freely extendable user interface, similar to the one featured on modular environments for audiovisual analysis and synthesis such as PureData (pd-extended [59]) and EyesWeb [29], that can be run on most laptops.

Additionally, guitarists have been developing a body language vocabulary adding a visual communication to their musical performance [8] (from full-body gestures to facial expressions). The multiple sensing methods available at a low cost nowadays, from remote cameras [5, 6] to built-in accelerometers among other sensors [40], would allow to better understand the gestural intention of the guitarist and emphasize hers/his musical expression, renaming the instrument an "augmented guitar" [41, 43].

B. From guitar learning towards educational games

Plenty of methods have been proposed to learn and teach guitar playing: from the academic study and interpretation of classical scores, to the more popular dissemination of guitar tabs providing a simplified notation, or teaching by playing within nomadic communities, playing by ear in an improvised music context, and so on... However, most of these methods require a long training before the user is proficient enough to become autonomous.

After efficiency, usability, ergonomics; an important factor when designing today's user interfaces is pleasurability. "Guitar Hero" [38], a video game featuring a controller inspired by a "diminished" [2] version of the guitar, consisting in having players challenge each-others in following a "4 on/off" note version of a guitar score, has recently caught a lot attention. Blend pleasure and learnability in educational games [21, 7].

II. Two subprojects, two applications

We proposed two sub-projects blended together in this project. While the first is aimed at artists and the second at "standard users", while the first would help create artistic performances and the second would enrich educational learning; we believed that these two projects share enough similarities among their work packages and deliverables so as to merge them together in a single eNTERFACE'09 project.

A. A gestural/polyphonic sensing/processing toolbox to augment guitar performances

The purpose of this subproject is to study and refine the methods employed in the sound analysis, synthesis and processing of the guitar and in the gestural expression of the guitarist, so as to provide a low-cost and opensource, software and hardware, toolbox that can allow guitarists to personalize their performance settings, from beginners to experts.

B. An interactive guitar score following environment for adaptive learning

The purpose of this project is to propose an open-source, community-based, standalone application to guitar players, from beginners to experts, for helping them to master musical pieces, with different adaptive layers of difficulty. The application would be used with real guitar to perform and follow a musical piece displayed on a screen, while a real-time polyphonic transcription of the guitarist's playing would allow the evaluation of its performance in an enjoyable way.

III. Artistic sub-project: Performance Toolbox

For this sub-project we decided to work on every part of the chain of the use of an augmented guitar :

- Audio analysis : how to use features of the guitar sound to detect events or to control parameters
- Gestural control : how to use movements made by the guitarist to add control on the sound the computer produces
- Audio synthesis : how can we enhance guitar performance with hexaphonic effects or not

As these categories are quite general, we decided to focus on the tools listed below :

- Polyphonic Pitch Estimation (see section III-A1)
- Fretboard Grouping (see section III-A2)
- Rear-mounted Pressure Sensors (see section III-B)
- Modal Synthesis (see section III-C1)
- Infinite Sustain (see section III-C2)
- Rearranging Looper (see section III-C3)
- Smart Harmonizer (see section III-C4)

To build and test these tools we used a Fender Stratocaster guitar with a Roland GK3 pickup [68] mounted on in and a String Port interface made by Keith McMillen [51]. Concerning the pressure sensors, as well as the wireless sensors interface, we used the ones from Interface-Z [31]. All the tools have been developped for Max/MSP [15] and/or PureData [59] environments.

A. Audio Analysis

1) Polyphonic Pitch Estimation: As mentioned in the introduction, there are several ways to capture the vibrations of the six strings of the guitar separately. Several sources point out that the crosstalk between strings is smaller using piezoelectric pickups than with electromagnetic ones, because the latter sees the magnetic flux in the coil beneath one string being influenced by the movement of adjacent strings. But we only had the possibility to test a GK3 hexaphonic magnetic pickup from Roland [68].

The YIN method by de Cheveigné and Kawahara [10, 9] is recognized as one of the most accurate pitch estimator when there is no background noise. While similar to autocorrelation, YIN uses a difference function that minimizes the difference between the waveform and its delayed duplicate instead of maximizing the product. Changes in amplitudes between successive periods will both yield an increase in the difference function. This compares to the autocorrelation function, known to be quite sensitive to amplitude changes, where an increase in amplitude tends to cause the algorithm to chose a higher-order peak and hence a too low frequency estimate; while a decrease in amplitude has the opposite effect. The introduction of the cumulative mean normalized difference function removes the need for an upper frequency limit and the normalization allows the use of an absolute threshold, generally fixed at 0.1. This threshold can also be interpreted as the proportion of aperiodic power tolerated within a *periodic* signal. A parabolic interpolation step further reduces fine errors at all F_0 and avoids gross errors at high F_0. We used the `yin~` external Max/MSP object developed at IRCAM.

In a paper dedicated to guitar patches [65] and also using the Roland hexaphonic microphone [68], Puckette, who wrote both `fiddle~` and `sigmund~` pitch extractors, both widely used within Max/MSP and PureData, suggests using the later. We found it was interesting to combine an time- with a frequency-domain pitch estimator. `yin~` gave overall better results, but we kept the possibility to combine it with `sigmund~` as they yielded close results during stable sections.

The pitch detection algorithm is based on `yin~`. Post-processing, based on the quality factor of `yin~` frequency extraction and on the level of each guitar string signal, allows to remove the spurious notes present mainly during transitions and when the volume fades out because of crosstalk between the strings. Though not critical in most conditions, the following parameters allow the user to fine-tune the pitch detection to his needs:

- Quality threshold: we didn't let a pitch estimate be taken into consideration while the average of the last quality factors was below a user-defined threshold.
- Level threshold: as the coupling between strings is shown to be higher from higher pitch to lower pitch strings than in the opposite direction [54], we defined a level threshold deviation per string, applied cumulatively from string to string.
- Outside range: an allowed range is attributed to each string, depending on the tuning and on an amount of

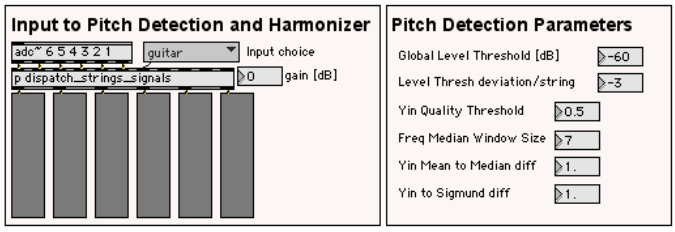

Fig. 1. *The view meters showing signals coming from the hexaphonic microphone on the left and the user parameters of the pitch estimation on the right*

Fig. 2. *There are five conditions that help the user tailor how notes will be cleared depending on his application.*

semi-tones per string. This allows to exclude notes that may be detected outside that range because of coupling or crosstalk.
- Mean-Median divergence, expressed in half tones, and median window size: the difference between the mean and the median of the pitch estimates over a user-defined window length is a good measure of pitch stability.
- YIN-Sigmund divergence, expressed in half tones, allows to limit note detection when an even higher stability is achieved, at the cost of a bigger latency. But it might be desirable in some situations.

One issue is to detect a note being played, but another one potentially as important is to detect the end of a note. There is no consensus about when a note is ended except the start of a new note. Several factors make it indeed a difficult task:

- Guitar strings, mainly the lower pitch ones have a very long decay. The pitch estimation algorithm can keep detecting a pitch with a good quality factor even when the sound of a string becomes masked by the other strings for the human ear.
- String coupling inherent to the instrument design [54] can have the effect of keeping strings vibrating, mainly open strings, as they keep receiving energy from the vibration of other strings.
- Crosstalk between the amplified string signals induced by the hexaphonic microphone, picking up the sound of adjacent strings, might give a reading even when the string doesn't vibrate.
- Depending on the application, one may want to keep the note living on one string until another note is played; for instance, to provide a synthetic or re-synthesized sustain.
- Fingers on adjacent strings, on the touch or near the bridge can inadvertently damp or re-trigger a note.

For all those reasons it was obvious that we couldn't provide a Fit them All method. Instead, we provide a comprehensive set of parameters that will define when a note is supposed to be considered ended. Conditions that will clear the notes are depicted in Fig. 2. Most of those conditions depend on parameters already tuned for the pitch detection:

- Quality: clears the note if the `yin~` quality falls below the threshold.
- Level: clears the note if the input level is below the level threshold associated with the deviation per string as explained above.
- Outside range: clears the note if its frequency evolves outside the range attributed to each string, something that might happen if the microphone crosstalk bleeds notes from adjacent strings.
- Mean-Median divergence: when a note dies or changes, its frequency changes and the difference between the mean and the median of the last values increase.
- YIN-Sigmund divergence: in the same way, only very stable frequencies yield similar results when comparing the `yin~` and `sigmund~` outputs. Putting a threshold in half-tones between both outputs allows to clear notes when instability occurs.

Those conditions have an effect both on the OSC note output sent to the *Fretboard Grouping* patch, on the synthesizer (currently a simple sawtooth oscillator followed by a resonant filter used only as a prove of concept) and on the harmonizer algorithm if *Mute harmonizer if cleared notes* is selected.

2) Fretboard Grouping: Hexaphonic pickups appeared in the 80's and were first aimed at making the guitar a synthesizer: some might want to put a bass sound on the 6th and 5th strings, an organ sound on the next two ones and then keeping the guitar sound for the last two strings. This is one example of what could be done with an hexaphonic pickup and an hexaphonic-to-MIDI hardware converter. Plugin that kind of pickup in software applications such as Max/MSP [15] and PureData [59] can expand the guitar sound effects string by string but allows more particularly to go even further in the segmentation of the fretboard. As an hexaphonic pickup directly provides a string-per-string control of the guitar, coupling it with a polyphonic pitch estimation as described below enables you to use the fret as the smallest element of your segmentation and to go deeper in the management of your fretboard. One can think in a "classical way" in terms of chords and scales or, in a more plastic way, in terms of fretboard zones and shapes (chord or geometrical).

The tool we made gives one the possibility to create groups of notes on the fretboard and then checks whether the played note(s) belong(s) to one of the defined groups or not. Using the example of the synthesizer guitar again, one can not only decide of the sound or effect to apply on only one string but on all the note of a defined group. Zones of effects can then be defined on all the guitar fretboard. We added a graphical visualization to this tool so as to have a graphical feedback for the created groups or for the played notes.

Another feature that our object handles is the possibility to detect if a group has been entirely played, meaning if all notes have been played without one extra note (not present in the

group) in between. Expanding a bit this entire played group property, we can then recognize whether the group has been played as a chord, as an arpeggio or as a simple group. A more detailed description of this feature is done afterwards. A specific chord or a specific note can then, for instance, be used to trigger sounds or change mappings, etc...

A first version of the tool has been made as Max/MSP and PureData patches. The final version has been written in Java in order to enhance the speed of the recognition and to make it easier to use as everything is gathered in one object to which messages are sent. The choice of Java as the language to write the Fretboard Grouping external was motivated by the development by Pascal Gauthier of pdj [23], a java external plugin for PureData. This plugin is based on the `mxj` Max/MSP object implementation and permits first to write external for PureData in Java (which was not the case before) and second, to use the same code to generate both Max/MSP and PureData external which was not the case when developing in C or C++. It has to be mentionned here that pd implementation via pdj external plugin hasn't been done yet.

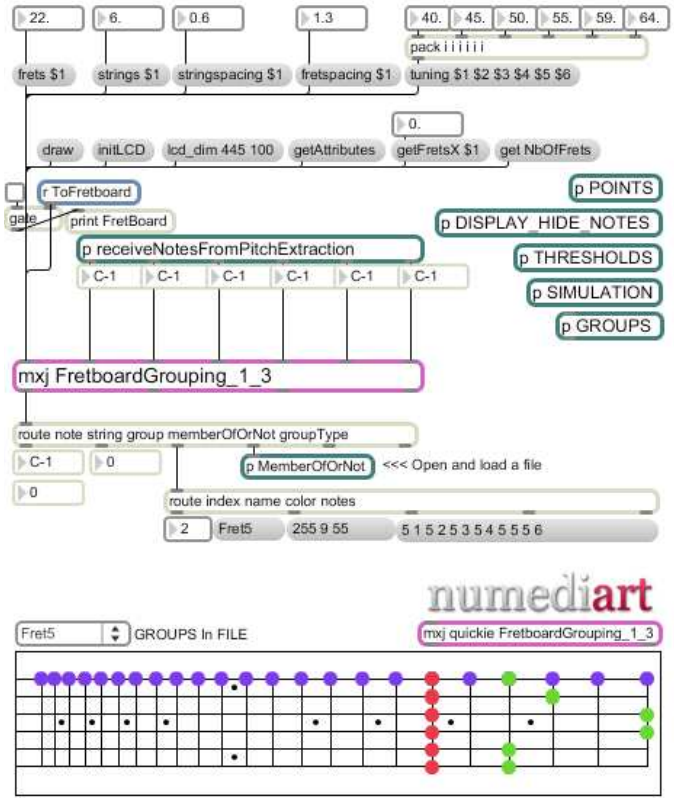

Fig. 3. Max/MSP help patch of the Fretboard Grouping tool

a) Graphical Visualization: We wanted to visualize the guitar fretboard considering its physical parameters (number of strings, number of frets and tuning), the groups the user is working with and the played notes detecting by the polyphonic pitch estimation. Several parameters are therefore customizable for the fretboard's display:

- the guitar parameters (as mentioned above) : number of strings and number of frets. The tuning parameter doesn't have a direct influence on the display, but enables the note to be displayed on the right scale.
- the display parameters : strings spacing and fret spacing factor. These factors can easily lead to a non realistic representation of the fretboard, but they can definitely be helpful to clearly see notes especially in the highest frets.

Other guitar fretboard visualization already exist. We can cite for example the Frets On Fire [39] game (free version of the Guitar Hero game) or the TuxGuitar [71] tablature editor and score viewer software. The second was the most suited representation as the first one gives a non realistic display of the fretboard.

As we wanted an easier integration with the Fretboard Grouping tool and as we first needed a quick implementation, we decided to developed the visualization part for the `lcd` object of Max/MSP environment. Only the visualization for the `lcd` object has been developed for the moment. Further investigations will be led on the OpenGL visualization tool that can be used in both software (GEM library for PureData [16] and `jit.gl.sketch` object for Max/MSP).

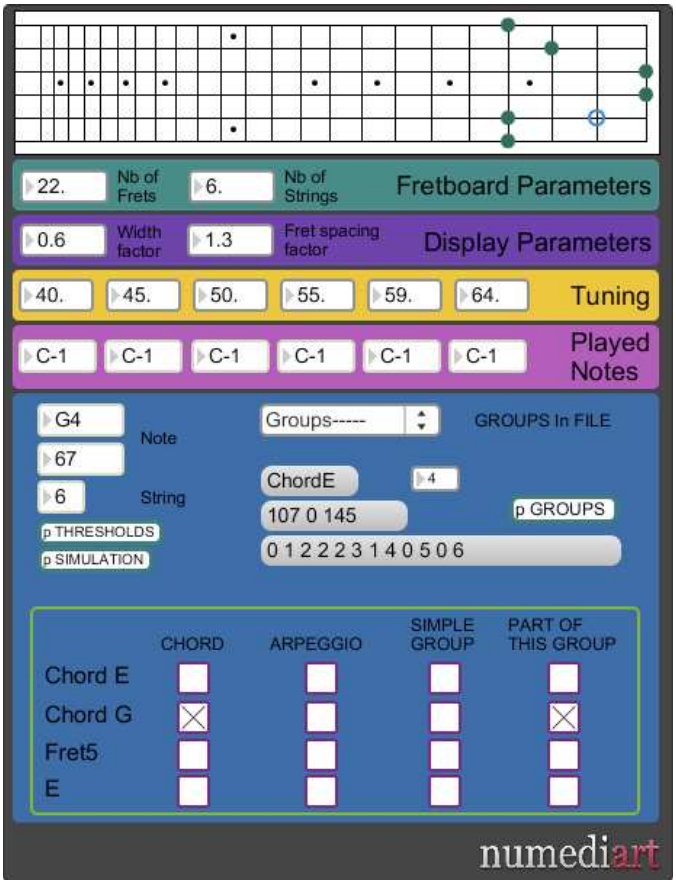

Fig. 4. Detection of the G chord

b) Groups: The construction of the groups one wants to work with follows these steps :

- played or selected (directly on the display of the fretboard) notes are added to the group
- when all the notes of the group have been selected, the group needs to be saved

- when all the groups are defined, the file, containing the groups definition, needs to be saved too
- read the file to use the groups

A display feature is accessible to give one the possibility to have a visual feedback of which notes are in the group.

Two parameters define a group : completeness and time. Therefor three types of group are defined :

- chords : all notes of a group are played (without extra-group notes) simultanesouly
- arpeggio : all notes of a group are played (without extra-group notes) not simultaneously but under a certain threshold
- simple group : all notes of a group are played (without extra-group notes) above a certain threshold

The discrimination between the different types of groups is, for the moment, based on the time factor. Two thresholds are then defined : one, discriminating between chord and arpeggio and the other one discriminating between arpeggio and simple group. If all notes of one group are played under this chord / arpeggio discrimination threshold the played group is recognized as a chord, if they are played above this threshold and under the arpeggio / simple group threshold it will be recognized as an arpeggio, and if it is below this last threshold, it will be recognized as a simple group. If notes are played interlaced with other notes (of other groups or not in any groups), notes are just recognized as part of the groups.

B. Gestural Control : Rear-Mounted Pressure Sensors

The basic premise of this gestural control subproject was to add pressure sensors to the back of an electric guitar in order to add another expressive control to the sound for the guitarist. We decided that one goal of this control should be that it should not require the player to spend much time learning the controller, but should feel like a natural extension of playing the guitar.

1) Sensors: Due to familiarity, we chose FSR pressure sensors to use for this implementation. They are well-known as reliable and easy to use. We made the decision to use their 4 cm square pressure sensors because we felt that they would cover more area of the back of the guitar. After some testing, it was determined that the 4 cm square sensors may have been more sensitive than necessary for this application, and the 1.5 cm round FSR pressure sensors might have been a better choice for both sensitivity and placement on the guitar body. This will need to be tested further in the future.

The sensors came with a prebuilt adjustment and op-amp circuit as well as an interface connector so that they could be used with an Interface-Z MIDI controller interface [31].

Due to familiarity, ease, reliability, and interoperability with the FSR pressure sensors, the Interface-Z was chosen as the interface between the physical sensors and the computer using a MIDI controller interface. The Interface-Z allows for up to 8 sensors which vary a control voltage between 0 and 5 volts to be translated into either a 7-bit or 10-bit MIDI controller value. Although the 10-bit controller value is split across two MIDI controllerrs. 7-bit resolution was chosen because it was sufficient for this project.

Pressure-voltage curves are supplied by the manufacturer to describe how the output voltage varies with supplied pressure. It was experimentally determined that for the pressure levels seen at the back of the guitar, the pressure sensors were operating nonlinearly. A $y = x^3$ mapping was implemented to linearize the output of the sensors.

An array of pressure sensors were chosen as the interface to use instead of a position sensor, because the array of pressure sensors could also provide total pressure as another control value It was unknown how many sensors would need to be included in the array to provide enough feedback for the type of control that we wanted. Initially tests were run using only two sensors, but after several players tested the system, we decided that three sensors would be more appropriate. A four sensor array was never tested.

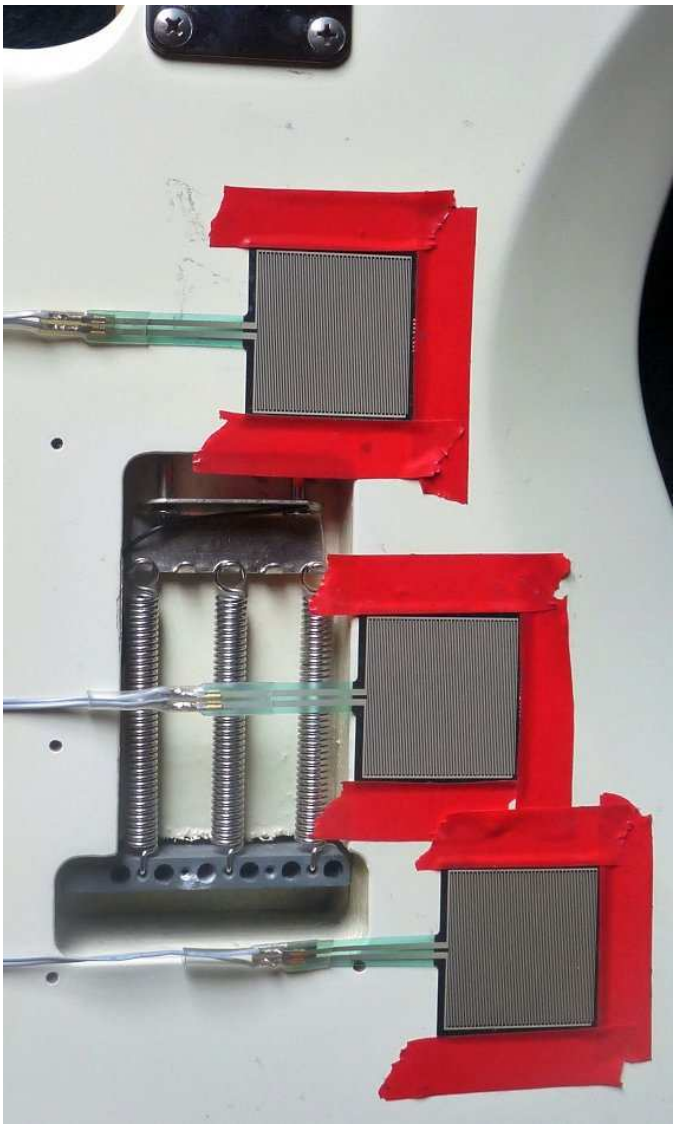

Fig. 5. Rear of the guitar with the three pressure sensors

By having several different guitarists test the three array system, we made two important discoveries: the system was extremely sensitive to the bodyshape of the player, and the playing position of some players often caused one of the

pressure sensors to be favored inappropriately. The solution which we found for this was to put a block of foam along the array between the guitar body and the player's body. This solution was excellent from a technical standpoint, but something more durable would need to be used for a longterm solution.

2) Mapping of Sensor Data to Control Values: In order to acquire the total pressure, p_{tot} from the array, the following equation was used.

$$p_{tot} = \frac{\sum_{i=1}^{n} p_i}{n} \tag{1}$$

where n is the number of sensors and p_i is the linearized control value representing pressure on an individual sensor. The center of pressure, P_c, along the array is given by a weighted average of particles as follows.

$$P_c = \frac{\sum_{i=1}^{n} p_i P_i}{p_{tot}} \tag{2}$$

where P_i is the position of an individual sensor. This equation is useful because the positions of the sensors do not need to be evenly spaced.

The velocity of P_c, v_c is derived using the following equation.

$$v_c = \frac{P_c(t + \triangle t)}{\triangle t} \tag{3}$$

where $\triangle t$ is 20 msec.

Control of effects and other parameters was tested using both this velocity and a derived acceleration. We decided that in this particular configuration using these higher order controls to directly control effects parameters was generally uncomfortable and unnatural, but using a velocity threshhold as a trigger for effects did feel natural. To allow for a natural velocity trigger, the threshhold values are different in the positive (or right-turning) and negative (or left-turning) directions.

After trying several different effects parameters, the choice made for the proof of concept video was the following.

- P_c is mapped to the center frequency of a bandpass filter. The range of P_c is mapped logarithmically between 600 Hz and 4000 Hz.
- p_{tot} is mapped to the Q of the same bandpass filter. The range of p_{tot} is mapped linearly to a Q value between 10 and 30.
- The velocity trigger is mapped to a gate to a delay line. The gate opens for 300 msec and the delay is set to 300 msec with a feedback factor of 0.8. The trigger values are -7.8 and 8.8 normalized pressure units per second.

These mappings provide an effective demonstration of the capabilities of the pressure sensor array as a sound/effects controller.

C. Audio Synthesis

1) Modal Synthesis:

a) Background: Acoustics guitars, naturally producing a certain level of sound thanks to their resonating hollow bodies, faced feedback issues once amplifiers were introduced. Solid-body guitars, first designed to solve these issues, are perceived by some players to afford less playing nuances due to the reduced mechanical feedback of their less resonating body, yet offering a more widespread palette of sounds. Christophe Leduc designed an hybrid solution: the *U-Guitar* [46, 47], a solid-body guitar with resting or floating soundboard. Guitars with on-board DSP such as the Line6 Variax allows the player to virtually choose several models of plucked stringed instruments on one single real instrument. Amit Zoran's Chameleon Guitar and reAcoustic eGuitar [76] allow the guitarist to redesign the instrument virtually (by digital methods) and structurally (by mechanical methods).

There has been much work in computer music exploring methods for generating sound based on physical simulation [32, 14]. With Modalys, also usable in Max/MSP, Iovino et al. propose to model an instrument by connecting elements and calculating the modal parameters of the resulted assembly [32], yet it is tedious to build complex models for any given geometry.

Penttinen et al. [60, 61] proposed a method for real-time guitar body modulation and morphing, which has been recently implemented in Matlab and C/C++ [73]. However, their method is based on digital signal processing, essentially for computational issues, and in particular maximal efficiency.

b) Theory: We propose to bring a physics-based approach to the multimodal guitar, so as to give control parameters that can be easily mapped to parameters from the sensors. For this purpose, we chose the modal analysis which consists of modeling the resonator, here the guitar body, with its vibration modes. The microscopic deformations that lead to sound are expressed as linear combinations of normal modes. Modal parameters, i.e., frequencies, dampings, and corresponding gains are extracted by solving the eigenproblem with the use of a finite element method (see, for example, [55] for more details). The sound resulting from an impact on a specific location on the surface is then calculated as a sum of *n* damped oscillators:

$$s(t) = \sum_{n}^{1} a_i sin(w_i t) e^{-d_i t} \tag{4}$$

where w_i, d_i, and a_i are respectively the frequency, the decay rate and the gain of the mode *i*. The method preserves the sound variety when hitting the surface at different locations.

In the multimodal guitar, the sounding guitar (the main body without the strings) is modeled through a modal approach. In a pre-processing, the modal parameters are extracted for each point on the surface. We chose the method described in [63] due to its robustness and multi-scale structure. It uses the SOFA Framework [30] to get the mass and stiffness matrices . Specific material properties and resizement can be set for the sounding guitar. Modal synthesis is especially well suited to model irrealistic objects.

During real-time, the resulted sounds are calculated through a reson filter (similar to [17]). Modal sounds can also be convolved with outputs of sensors on the fly, giving the user extended flexibility for interactive performance.

Fig. 6. Screenshot of an acoustic guitar modelled in the SOFA Framework

c) Interacting with modal sounds: Using the C/C++ code for modal synthesis of bell sounds from van den Doel [18], we implemented a flext object [27, 28], thus compliant with the PureData and Max/MSP environments.The purpose of this tool is to provide more experience with modal sounds. In this manner, interesting sounds can be easily obtained by convolving modal sounds with user-defined excitations.

2) Infinite Sustain: The guitar is an instrument with a relatively short sustain (compared to for ex. wind instruments). The electric guitar has addressed this problem with various methods; overdrive, compression and feedback. In our application, we use additive and granular synthesis to create a continous sound from a detected note or chord.

The Infinite Sustain tool goes through these steps :

- Attack (”note on”) detection with Max/MSP `bonk~` object
- Spectral composition analysis of the detected note at 2 points (attack time + 100ms and 120ms)
- Synthesis of the sustained note using the 2 analysed spectrums (additive synthesis with Todor Todoroff’s `add_synthw~` object)
- Synthesis of a granular sustained tone using the `munger~` object [3, 4] rewritten using flext object [27, 28]
- Mix of the two synthesis methods to create a lively sustained tone, with lots of timbral variation possibilities
- A tilt sensor controls the sustained tone playback volume

3) Rearranging Looper: Loop pedals are often used in a performance context to create sound textures and grooves. One can be frustrated with the static quality of the looped audio; the same loop is played over and over again, leading to boredom and to aesthetic similarity in mixed music performances. We wanted to create a looper which could rearrange the recorded audio. The program works like a beat slicer: the incoming

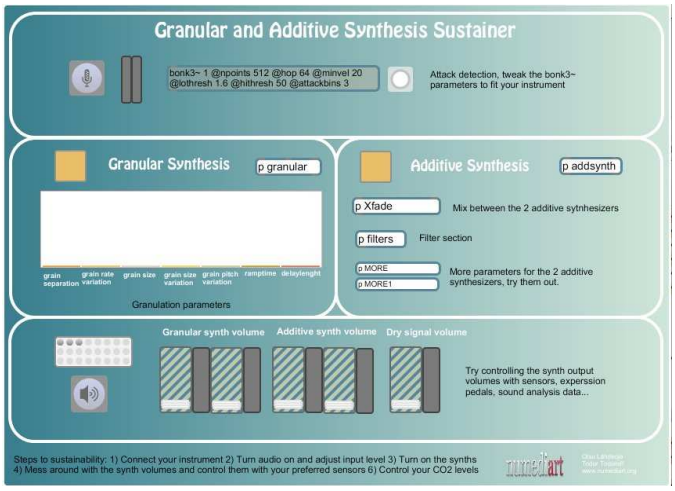

Fig. 7. Screenshot of the Infinite Sustain tool

audio is analysed looking for attacks. An “event map” is created according to the attack times. The events may then be played back in any order. In this first version of the tool, the playback options are straight, backwards, and a specific random factor ranging from 0 to 100. With random 0 the playback stays true to the recorded audio, with random 100 the audio events are played back totally randomly, creating a sonic mess highly inspiring.

The Rearranging Looper tool goes then through these steps:

- Record on and off activated by a 1-axis accelerometer on the guitar’s head
- Write to a buffer, create a temporal event map with attack detection (`bonk~` object)
- Playback from the buffer
- Adjust behavior; playback mode and randomness

The program is in its first version and will evolve towards more complex/interesting playback behavior, controlled by the player via sensors and playing.

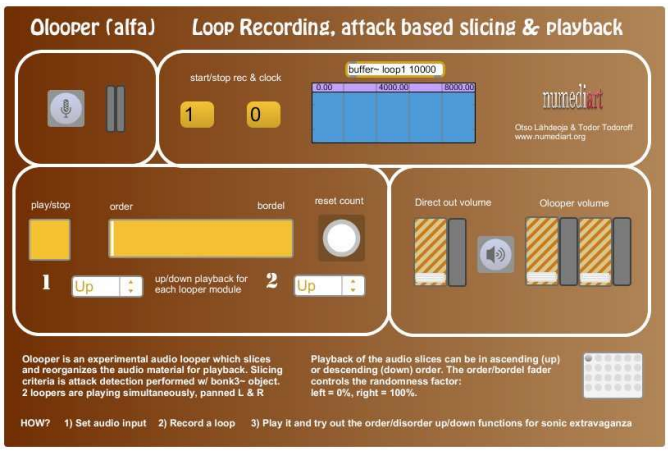

Fig. 8. Screenshot of the Rearranging Looper tool

4) Smart Harmonizer: The ability to know the exact note being played before harmonizing, thanks to the hexaphonic pitch extraction algorithm described above (section III-A1), opens new interesting possibilities. In the framework of tonal music, those possibilities start with the choice of a scale, referenced to a base or root note. We have implemented some common scales like major, minor natural, minor harmonic, minor melodic ascending and descending. Currently, there is a `coll` object that loads a file containing the intervals in half tones within an octave for each defined scale:

```
major, 0 2 4 5 7 9 11;
minor_natural, 0 2 3 5 7 8 10;
minor_harmonic, 0 2 3 5 7 8 11;
minor_melodic_asc, 0 2 3 5 7 9 11;
minor_melodic_desc, 0 2 3 5 7 8 10;
```

The selected set of intervals, chosen by name with a menu, are repeated over the whole range of MIDI notes, starting from the root note defined by the user, and stored in another `coll` object containing all the notes of the chosen, now current, scale that will be used by the harmonizer. More scales can be defined by the user and it would also be quite easy to define a set of notes that don't repeat at each octave, simply by loading in the current scale `coll` a list of notes belonging to the set contained in a text file. Those sets could be defined using a virtual keyboard, a MIDI or OSC input, defined with the *Fretboard Grouping* tool, or simply in a text editor.

In order to define how to harmonize, we also need rules to modify the desired intervals depending on whether or not the harmonized note with the desired transposition factor is part of the chosen scale. Therefore we use the following rules, also stored in a text file loaded by a `coll` object, where the first interval is the preferred one, and the second, the choice if the first fails to transpose the note within the chosen scale:

```
unison, 0 0;
second, 2 1;
third, 4 3;
fourth, 5 6;
fifth, 7 6;
sixth, 9 8;
seventh, 11 10;
octave, 12 12;
```

In order to augment the flexibility of the program, those first and second intervals can be freely entered by the user, including fractional half-tones. Though the two proposed choices in the predefined intervals will always yield at least one note in the scale for traditional western scales, it may not be the case for non-western ones or with non-integer half-tones. Therefore we added a third choice (see Fig. 9). Experiments with a viola player and quarter or eight-tones yielded very surprising and interesting results. But the availability of three levels of choice allow also to force an interval by specifying three times the same one, or to allow only one interval if it fits within the scale and no transposition otherwise, by specifying the desired interval as the first choice and 0 for the second and the third ones. We also added the possibility to shift the result one octave down or up with the red menu (-, 0, +) at the right of the interval menu. The actual harmonization is done with a combination of the `psych~` and `gizmo~` objects whose levels may be adjusted differently for each string. We kept the two algorithms, the first in the time domain and the second in frequency domain, as they do sound quite differently. And, at almost no cpu cost, one may define two additional sound transpositions with `psych~`. This can be used for chorus-like effects or for octave doubling.

Thus, using the knowledge of the played notes, a scale or a set of notes, and rules determining the desired harmonization factor depending on the formers, we defined an adaptive transformation, depending on the input notes. And different intervals or rules may be applied individually to each guitar string.

We described how the transposition factor can be chosen in a smart way, but there are times where one wants to mute the output of the harmonizer. We implemented the following mute functions:

- *Mute input notes outside the chosen scale*: if the played note is not in the scale, there will be no harmonizing.
- *Mute output notes outside the chosen scale*: if the input note transposed following the user-defined rule doesn't fit in the chosen scale, it won't be harmonized.
- *Mute output notes outside range*: a range is defined for each string, from the lowest note playable on that string (the tuning can be easily defined) to that note transposed by a user-defined amount of semitones; if the harmonized note would fall outside the range, it isn't harmonized.
- *Mute harmonizer if cleared notes*: the pitch extractor has parameters that define what conditions stop the note. the harmonization can be muted when a clear note condition is met.

We might also want to prevent some played notes to be heard on some strings. That would for instance be the case if some string/note combinations are used as a kind of program change, to change a preset that would for instance change the scale or the harmonizing choices. This hasn't been implemented yet.

Finally, it is possible to *Harmonize using float pitch detection*: the harmonized note is "retuned", that is, transposed to the closest tempered scale note, by taking into account the detected deviation from the tempered note given by the pitch extractor. Besides allowing the harmonizer result to be exactly in tune, it opens another interesting application: if the harmonizing interval is set to unison, the resulting note can create beatings in regard to the played note when the string is bent, or simply thicken the sound as no played note is exactly in tune, and as the deviation in cents from the perfect tuning evolves over the duration of a note.

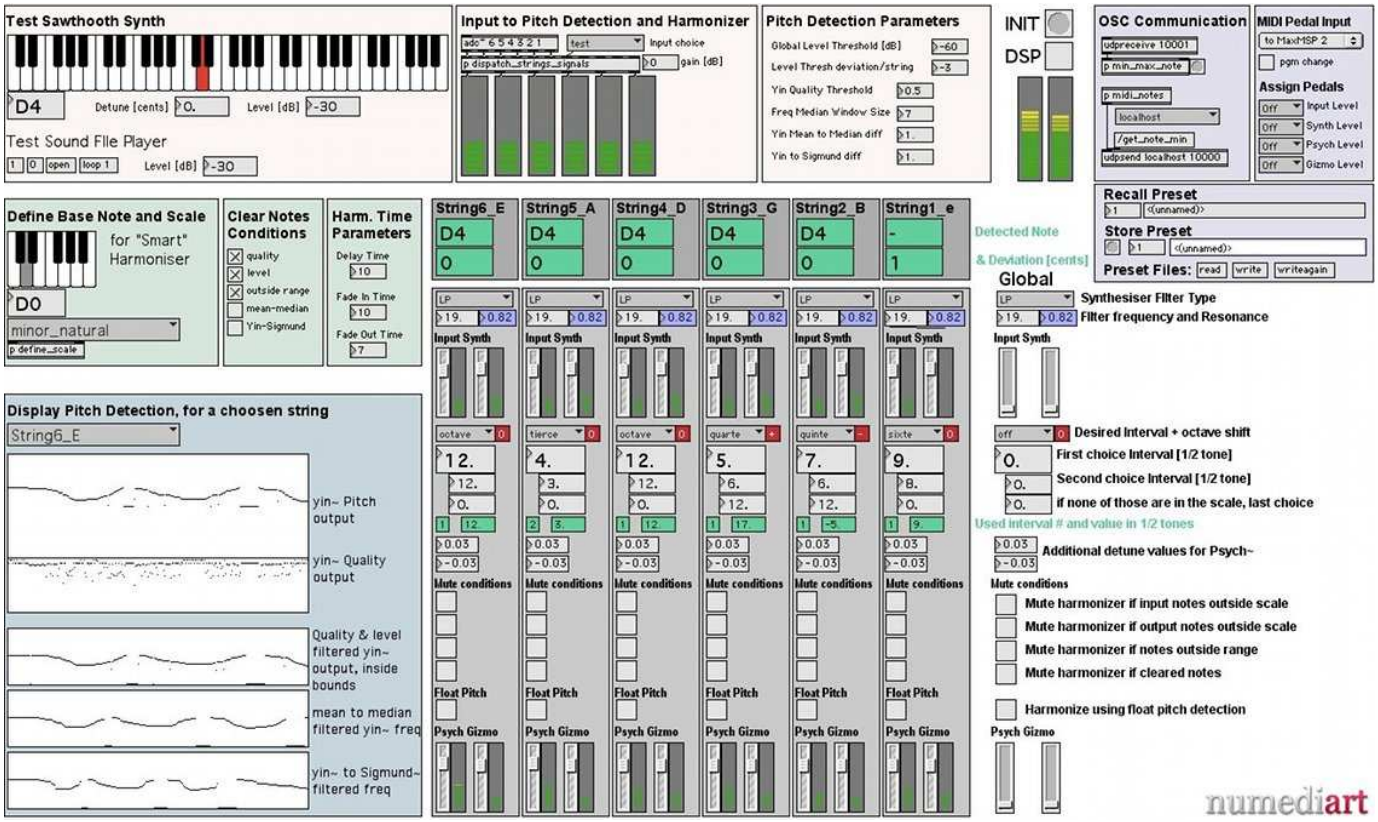

Fig. 9. Shown here with a synthetic test tone, the Max/MSP patch that extracts the pitches independently for each string, using an hexaphonic microphone, and harmonizes the played notes in a smart way, i.e. taking into account the notes being played, a chosen scale and desired intervals defined independently for each string.

IV. Edutainment sub-project: Study Workbench

Knowing that fitting an hexaphonic pickup requires a structural modification of the guitar, will it help enhance the ergonomics (non-invasiveness) and allow a better performance in terms of signal processing? Should we use a low-cost alternative that requires a webcam to analyse the guitarist's gestures using computer vision techniques [5, 6] and a monophonic guitar sound, so that to extract all the necessary information of both methods through multimodal fusion [66]? In the following part, we will narrow down the scope to focus on the multimodal musical transcription.

The precursor of the multimodal musical transcription is Gillet's work transcribing drum sequences [25], where joint features are used. Ye Wang borrowed the philosophy of the audio-visual speech recognition to try to realize the violin transcription based on the weighted sum of ouput values of modalities [72]. They both show the trend and promising future of multimodal transcription. Garry Quested and Marco Paleari separately proposed different methods on the guitar with various modalities and deterministic fusion methods [66, 58], where [58] produced 89% of the recognition rate. However, their simple deterministic nature of the fusion schemes fails to handle missing samples in audio and dropping frames in video, which are always an issue in the real-time application, and unexpected output of modalities. Hence, the recorded experiment data requires no information loss, which leads to the demand of very expensive high end recording equipment and unaffordable computation load for a real-time application. Moreover, the static weights on each modality in the fusion scheme do not allow the system to adjust according to the reliability of modalities, such as change of lighting condition to cameras, and our crucial objective—user skills.

Considering their experience and working towards a real-time audio-visual system of the multimodal musical transcription, we build the system with the following characteristics:

1) Have low-cost hardware and software setup
2) Provide reliable real-time modalities
3) The audio modality is the main source of the information (see section IV-B), while the video modality provides supplementary information (see section IV-C)
4) Provide low information loss by building a stable data acquisition approach (see section IV-E)
5) Have a probability-based fusion scheme to handle missing data, and unexpected or misinterpreted results from single modalities to have better multi-pitch transcription results (see section IV-D)
6) Include the updatable weights of each modalities in the fusion scheme to allow system to adjust according to users and reliability of modalities.
7) Visualize simultaneously the guitar score and feedback from the score following evaluation (see section IV-F)

A real-time system of the multimodal musical transcription mainly consists of three parts: data acquisition, modality construction, machine learning and multimodal fusion. In

the following sections, we first introduce our design and implementation of the overall system, and then detail them right after that.

A. System Overview

In our system, two webcams and a finger tracking algorithm form the video modality, soundcard and a polyphonic pitch estimator form the audio modality, and finally a multimodal algorithm fuse these two modality, shown in the top figure of Fig. 10. A recording is system is also necessary during all the process from design and fine-tune modalities, to multimodal fusion mechanism design, shown in the bottom figure of Fig. 10. The system hardware overview is shown in Fig. 11, where we adopts the most common and low-cost devices, including:

- 1 laptop with Microsoft Windows XP
- Two USB Logitech webcams (two concurrent high speed Sony PS3 Eye cannot currently run at the same time on the same computer)
- 1 Line6 Variax 300 guitar
- 1 TASCAM US-144 USB soundcard
- 1 external FireWire/USB hard-drive for storing offline training data (non-necessary for the final system)

We also use an ARToolKitPlus [1] marker on the guitar headstock and colored markers for fingertracking on finger nails.

The problem now urns to choose a open source/low cost platform which can provide stable, simple, and quick development on data acquisition, modality construction, and machine learning and multimodal fusion, where any of them requires tedious work and complicated analysis process, based on our low cost hardware setup. EyesWeb [29] from InfoMus Lab, DIST-University of Genova, has been a very successful platform for audio-visual real-time applications since 1997, providing an intuitive visual graphical development environment and powerful support without charge. Pure Data is also another effective open source real-time graphical programming environment for audio, video, and graphical processing [59]. However, they can not easily make lossless synchronized recording using multi-cameras and one microphone at the same time. Their lack of support of easily integrating programs in various languages slows down the early prototyping process.

OpenInterface [44, 45], developed by TELE Lab, University of Louvain, is an ideal choice in our application, which allows to fast prototype real-time multimodal interactive systems (or online system with constant delay), and implement synchronized raw data recorder. It provides a graphical programming environment and interfacing programs in all the main-stream programming languages such as C/C++, Java, Matlab [50] and .NET. Shown in Fig. 10, all of the data acquisition, finger tracking, pitch estimation, and multimodal fusion algorithm, and recording function is implemented in OpenInterface.

Providing higher abstraction and statement power, Matlab allows programmers to design and implement algorithm more easily and faster. Thanks to the easy integration of the Matlab engine by OpenInterface, we can easily have a recording system of raw data, quickly integrate an "online" complete

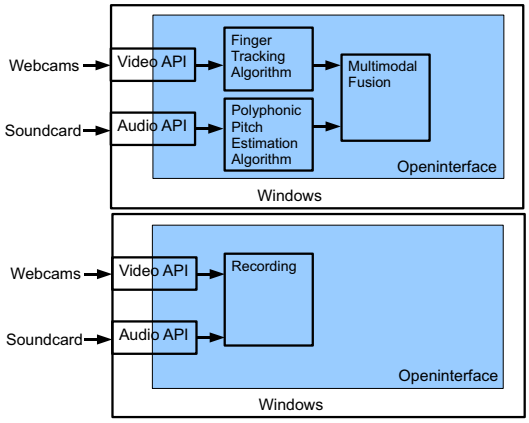

Fig. 10. System Software Architecture Overview. Top: Runtime. Bottom: Recording

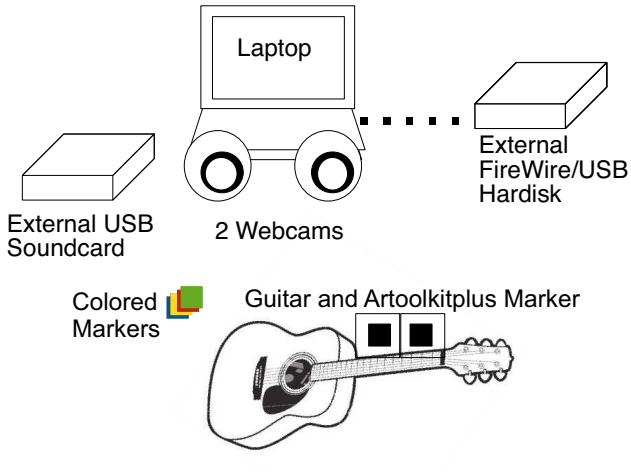

Fig. 11. System Hardware Overview

system with a short constant delay, and comfortably display the results. Our finger tracking and pitch estimation algorithm implementation also benefit from the same fact.

Our system diagram using OpenInterface both for online and offline recording is shown in Fig. 12, including the multi-cameras, audio, and ARToolkitplus components. Except the other components for video-driving strict synchronization, the Matlab processor component calls recording function of raw data, finger tracking, and pitch estimation algorithms in Matlab.

B. Audio Analysis: Polyphonic Pitch Estimation from a Monophonic Signal

1) Background: As opposed to the method proposed in section III-A1, we wanted to perform an estimation of the fundamental frequency of each note played by the musical instrument without using expensive or non-factory devices such as hexaphonic pickups, not available on most affordable guitars.

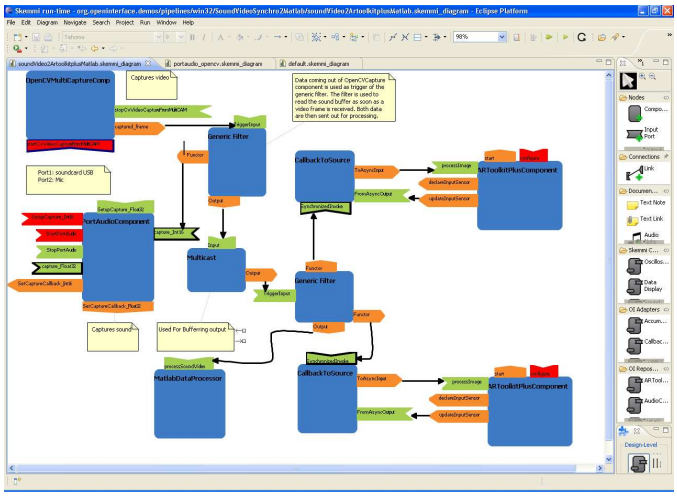

Fig. 12. System Diagram (online and offline recording) using OpenInterface [44, 45]

The third running of the annual Music Information Retrieval Evaluation eXchange (MIREX) [19] gives an up-to-date overview of methods and algorithms for multiple fundamental frequency estimation & tracking (see the contest results here [53]), yet it focuses on accuracy of the results, thus algorithms don't need to run in real time, a mandatory feature for our system.

Due to the limited time available, we decided to use methods that we already implemented, whose source code was available, and which were designed to work in real time.

Klapuri's method [37] doesn't implement polyphony estimation, but the output salience values can be used to estimate polyphony (eq.(8) in [37]). The polyphony estimation is not very reliable however, especially if levels of component sounds vary (not equal levels).

Arshia Cont's realtime algorithm [13] is based on a non-negative sparse decomposition of the incoming signal as a product of two matrices:

- the first matrix is filled with the spectrum of all the single notes that the instrument can produce, the notes being recorded offline one-by-one so as to train the system;
- the second matrix, a vector, indexes all the notes that are detected in the audio signal, containing a high value at each row that corresponds to each detected note, a low value for all other non-present notes.

As sound is harmonic by nature, harmonics can overlap between notes. "Sparse" means that the whole playing should be described by the smallest number of note components, given a predefined maximum number of decomposition iterations. Arshia Cont offers for free his algorithm as a `transcribe~` [13, 12] object, for Max/MSP [15] and PureData [59]: to our knowledge, it is the only realtime implementation available, for free, working inside the opensource PureData modular environment.

O'Grady and Rickard also proposed an algorithm based on non-negative matrix decomposition, but running offline and requiring an hexaphonic pickup [56].

2) Implementation: We used Arshia Cont's realtime algorithm. In order to have the algorithm work with guitar sounds, we had to record guitar notes one-by-one so as to train the algorithm, using the Matlab code Arshia Cont provided us.

We modified the C++ `transcribe~` [13, 12] flext object [27, 28] object and the Matlab template training source codes so as to exchange template files between the two using MAT files, instead of the former text files that caused us issues with parsing on different OS platforms. We used libmatio, a LGPL C library [49]. Additionaly to the template matrix contained in the template file, we added metadata that is written on the MAT file after the template training and loaded and parsed in the flext object:

- `lowest_midi_pitch` (21 for piano, 40 for guitar, 38 for "Drop-D" guitar), defining how the pitch list is indexed;
- `fft_size` and `hop_size` for a consistency check (MAT file and the `transcribe~` object settings values won't match, the user is adviced to change the object settings)
- (optional) `instrument`, `author`, `institute`, `date` and `email` for further contacts

We hope that Arshia Cont will integrate our modifications to the next `transcribe~` release. Note that everything in the chain can rely on free software as the template training works as well with Octave [26].

Due to the fact that this algorithm has been shown to provide accuracy of at most 88% [11] for the piano, visual modality should help increase the robustness of the pitch transcription and provide extra information such as identifying which strings have been played.

C. Computer Vision Analysis

As a role to provide finger positions and complement the audio modality, we survey the literature and seek a robust method, which should estimate the three dimensional position of four fingers—the two dimensional position above the fingerboard plane and the distance between fingers and the fingerboard. [74] detected fingers on the violin by using the Condensation algorithm [34], in which the joint finger model dynamics and the Gaussian skin color model are employed. However, for the note inference, it does not provide satisfying results (14.9% full-matches and 65.1% partial matches between audio and video results), perhaps because of lack of another camera to provide three-dimensional information.

We adopt a method based on Chutisant Kerdvibulvech's work which made use of two webcams and an integration of the bayesian classifier, ARTag, and Particle Filtering and colored markers to provide four finger three dimensional positions relative to the marker mounted on the guitar [36]. Though Chutisant Kerdvibulvech's paper does not provide scientific evaluation of precision under a large scale test, which is one of the drawbacks and challenges to adopt this method, his survey based on several user survey did showed a subjective positive tracking result.

In his method, the ARTag marker appearing on the images is used to calculate projection matrices used later in the tracking

algorithm to map the three dimensional guitar coordinate into two dimensional image coordinate [36]. Bayesian classifier and image processing techniques form a probability map for each pixel of the whole images using pre-trained classifier and adaptive classifier, which is used to reduce the impact from slight change of the lighting condition [36]. Combining these parameters, particle filtering tracks finger markers by generating particles in a three-dimensional guitar coordinate system, and has them mapped onto the two dimensional coordinate using the projection matrices given the probability map as weights on each particle, and finally obtain the average finger markers three-dimensional positions. Two images are used to enhance the precision of the results [36].

Based on the main concepts, we re-implement this method with some modifications: Instead of using ARTag to calculate the projection matrix for calibration of the guitar position, we make use of ARToolKitPlus [1] due to its advantages of high recognition performance, free charge, and the lack of availability of ARTag. Image processing techniques also have been modified. The simplified structure of our implementation has been shown in Fig. 13. The tracking result is shown in Fig. 14. Since we use OpenCV as a main interfacing for video acquisition, the maximum frame rate we can reach is 15 fps due to the limitation of the OpenCV.

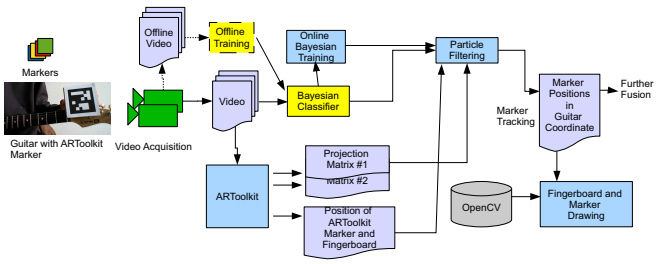

Fig. 13. Our Finger Tracking Implementation

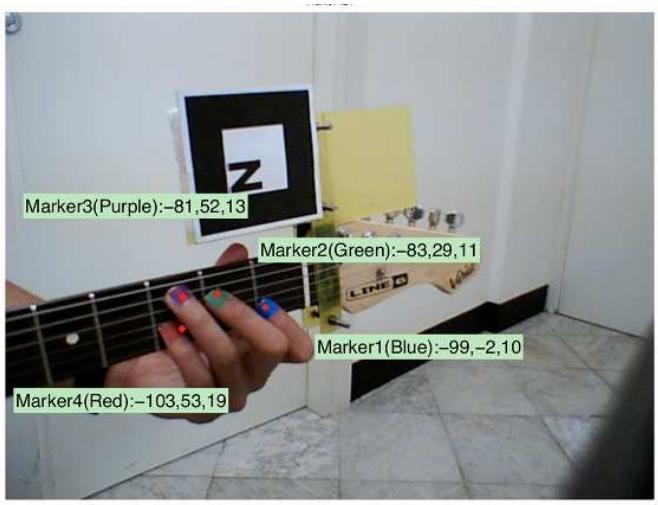

Fig. 14. Tracking Result of Our Implementation

D. Multimodal Fusion and Mapping Scheme

1) State-of-the-art: Since each modality has its own recognition in each modality, we should choose one among methods of intermediate fusion. The intermediate fusion methods, like probabilistic graphical model methods, such as Bayesian networks, can handle the imperfect data, generate its conclusion so that its certainty varies according to the input data [35]. Bayesian Networks or Dynamic Bayesian networks is very suitable for fusing our noisy or sometimes even missing results of locating finger position and audio pitch recognition results. Hence, for the fusion method, we adopt the Bayesian Networks method here. In our proposed scheme, weights of each modalities, representing the reliability of each modality, and majority vote techniques are included. The overall system is shown in Fig. 15.

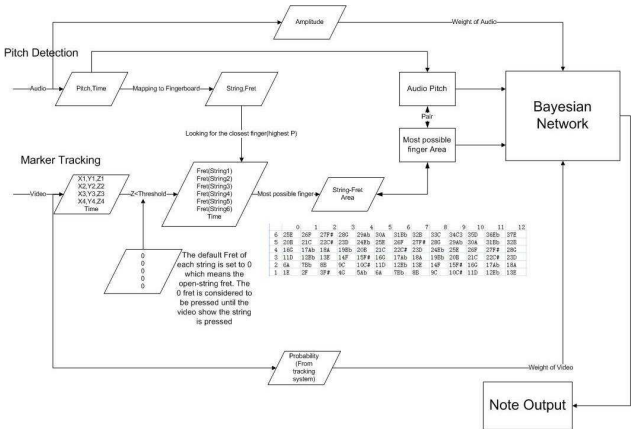

Fig. 15. Overall Fusion Scheme

2) Preprocessing system: In order to produce the best reasonable finger-pitch pairs to train and test the Bayesian Networks (BN). We need first to synchronize the recognition streams of the two modalities, and then the paring process is needed as the proposed system is a multi-pitch score follower, where more than one finger is tracked and maybe more than one pitch may be played at the same time.

3) Synchronization problem of two modalities: For the video modality, the frame rate is fixed as $30fps$. For the audio modality, consisting in estimating the fundamental frequency of each note played by the musical instrument, we used Arshia Cont's realtime algorithm [13]. The frame rate of informative data stream produced from this algorithm is not fixed. It presents the pitch and its amplitude when there are one or more onset(s) are detected. Thus we use these onset signals as the signs of synchronization. When there is an onset appearence at time T_P, we look for the closest T_F from the video frames and the corresponding frame F_{T_p}. Then we group the pitch happened at T_P and fingers positions from frame F_{T_p} together and mark these groups by T_P.

4) Event pairing problem of synchronized data: After the synchronization processing, now we have the temporal groups containing the data from the audio and video modalities. What we do following that is to pair the pitch data with the most probable finger that played this pitch. In order to do that, we

first mapping the pitch to the guitar finger board area according to Fig. 16. As a single pitch could be related to three String-Fret combinations in maximum, we list all possible String-Fret combinations down.

Str \ Fr	0	1	2	3	4	5	6	7	8	9	10	11	12
6	25E	26F	27F$_\sharp$	28G	29A$_\flat$	30A	31B$_\flat$	32B	33C	34C$_\sharp$	35D	36E$_\flat$	37E
5	20B	21C	22C$_\sharp$	23D	24E$_\flat$	25E	26F	27F$_\sharp$	28G	29A$_\flat$	30A	31B$_\flat$	32B
4	16G	17A$_\flat$	18A	19B$_\flat$	20B	21C	22C$_\sharp$	23D	24E$_\flat$	25E	26F	27F$_\sharp$	28G
3	11D	12E$_\flat$	13E	14F	15F$_\sharp$	16G	17A$_\flat$	18A	19B$_\flat$	20B	21C	22C$_\sharp$	23D
2	6A	7B$_\flat$	8B	9C	10C$_\sharp$	11D	12E$_\flat$	13E	14F	15F$_\sharp$	16G	17A$_\flat$	18A
1	1E	2F	3F$_\sharp$	4G	5Ab	6A	7B$_\flat$	8B	9C	10C$_\sharp$	11D	12E$_\flat$	13E

Fig. 16. Pitch-Finger board mapping table

Then, we need to map the finger data (X, Y, Z) to the corresponding String-Fret as well. In guitar playing, there are six notes that can be played without pressing any fret. They are called 0-Fret notes and they appear commonly during the guitar playing. In the cases that a 0-Fret note is played, it is highly possible that no finger would be tracked on the corresponding 0-Fret area. Our solution to this problem is setting the default frets that are pressed on all strings to 0 at each video modality frame. Then a later modification is made when the finger position data (X, Y, Z) indicates so. When we deal with the finger data (four fingers in maximum) in a temporal group. We look at the Z first. If Z is smaller than or equal to Z_{th} , then we map the corresponding X-Y pair to the String-Fret combination to change the default fret(which is 0) on that string. The Z_{th} here means the threshold Z of pressing. If a Z is smaller than Z_{th}, we consider this finger as in the pressing status. In our case, we chose 8 mm as the Z_{th}. During the mapping from X-Y pair to String-Fret combination, we use the idea of 'area' to classify the finger position. The 'area' of 'string S_A and fret F_B' is defined as from the midpoint of S_{A-1} and S_A, Mid(S_{A-1}, S_A), to Mid(S_A, S_{A+1}) vertically and from Mid(F_{B-1}, F_B) to Mid$(F_B$ and $F_{B+1})$ horizontally. In the case of first string or zero fret, we use Mid(S_2, S_1) and Mid(F_1, F_0) as the low vertical boundary and left horizontal boundary respectively. The distance from the nut to the n^{th} fret can be expressed as

$$D = L - \frac{L}{2^{\frac{n}{12}}} \tag{5}$$

So the distance from the nut to the midpoint of n^{th} and $(n+1)^{\text{th}}$ fret can be expressed as

$$D_m = (1 - \frac{1 + 2^{\frac{1}{12}}}{2^{\frac{n+13}{12}}})L \tag{6}$$

In our case, L is equal to $640mm$ and the distance between two strings is $7.2mm$ in average. Due to the lack of absolute parallelism of six strings, the square area we use here is an approximate one. In order to achieve higher accuracy, we are going to use Neural Networks as the nonlinear transformation function between X-Y and String-Fret in the future improvement. As this is the proto type of system and the lack of parallelism is so little, we will use these square areas for now.

After we scan all the finger data in one temporal group, we will have six Fret-String combinations from video modality and in maximum three Fret-String combinations from audio modality from that group. Then, we calculate the closest (highest possibility) finger that related to the pitch. Now, we have the pitch that is played and the related finger area ready for the BN.

5) Fusion System: Bayesian Network: Inspired by [52], we created a Bayesian network as our fusion scheme, shown in Fig. 17. According to [52], a Bayesian network over universe U with observed evidence e is expressed in the following equation:

$$P(U, e) = \prod_{A \in U} P(A|pa(A)) \cdot \prod_i e_i \tag{7}$$

where $P(U, e)$ is the joint probability of U and e, and $pa(A)$ is the parent set of A. In our network, the observed evidence e is the observed outputs from the pitch detection, the frets and strings from the finger position tracked, as well as their corresponding weight. The evidences are represented by the nodes Pitch Detected (PD), Fret Detected (FD), String Detected (SD) and their corresponding weight is represented by node WA and WV respectively. Note (N), Fret(F), String(S) and Image(I) are the unobserved variables. The Combination Played node (C) is the played score and the fret as well as string that player used which we are trying to find. Each arrow represents a conditional probability. The values of the observed evidence are represented by $PD = pd$, $FD = fd$, $SD = sd$, $WA = wa$, and $WV = wv$, respectively. The inference equation is then derived as:

$$\begin{aligned} P(C|N, I) =& P(Pd) \cdot P(wa) \cdot P(fd) \cdot P(sd) \cdot P(wv) \\ & \cdot P(N|PD, W_a) \cdot P(F|fd, wv) \\ & \cdot P(S|sd, wv) \cdot P(I|F, S) \end{aligned} \tag{8}$$

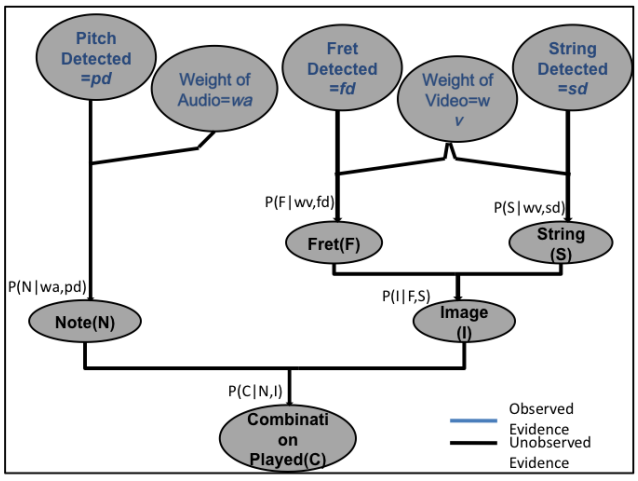

Fig. 17. The Bayesian Network Diagram

6) Modality Weight Computation and Majority Vote: Before we feed the data to the BN, the Modality Weight WA and WV reflect the reliability of the two modalities and how much they affect the fusion result. WA and WV are decided by two factors: modality failure detection and modality reliability.

Modality failure detection try to detect if the device is failure: if either audio or video signal within a time frame has no values, then the modality should be give zero weight until non-zero signals are detected.

It is not easy to determine reliability of the each modalities, though many parameters in the algorithm of the two modalities provide limited clues. Hence, instead of having an explicit setup of the weights of the two modalities, by the concept of majority vote, we can generate several reasonably distributed sets of weights. They are multiplied by corresponding failure detection result and then normalized. Each pair of weights will lead to a specific classification results in the Bayesian network, and the result of the majority is our final result. It provide a way to avoid calculating weights explicitly, which might not improve or even degrade the performance of the system.

E. Data Recording for Training

While our aim is to recognize multiple notes at the same time, it is reasonable to first reach the single note recognition and the the two note recognition as our preliminary goals. We further limit the range to recognize notes into first 30 positions, that is, from $1E$ to $29A_b$ in Fig. 16. To train the system, at least 10 pairs of video and audio information in each class should be recorded. We have made 300 data samples for single notes, while having to make 10 notes for each common frequent pair(should be much less than $C_2^{30} \cdot 10 = 4350$).

In the recording setup, projection matrices from two images are computed, synchronized, and stored together with an audio vector of 4096 samples in 44.1 kHz, and two images in the size of 288×352 in the same data packet. All these data will be fed to the following recognition algorithm to produce the results. The two images with the ARToolKitPlus [1] output are shown in Fig. 18. The runtime display of the recording system is shown in Fig. 19, where sound samples, projection matrices are drawn at the right hand side using the function of Matlab.

F. Visualization

1) Available guitar score visualization tools: So as to provide both a visualization of the score to be played by the guitarist and visual feedback on how accurately the score is actually played by the guitarist, we initially planned to modify an open-source equivalent of the *Guitar Hero* video game, named Frets On Fire [39], because of its engaging and fun visual interface. While we are still in the design phase of our system and it can not yet estimate in real time the accuracy of the guitar playing, we needed to use a tool that assisted us for the recording of the system training database and the testing of the system. A guitar score visualization application such as TuxGuitar [71] is better aimed for that purpose, as it allows to browse the score backwards in time once the score has been played and annotated. Once the real time implementation of

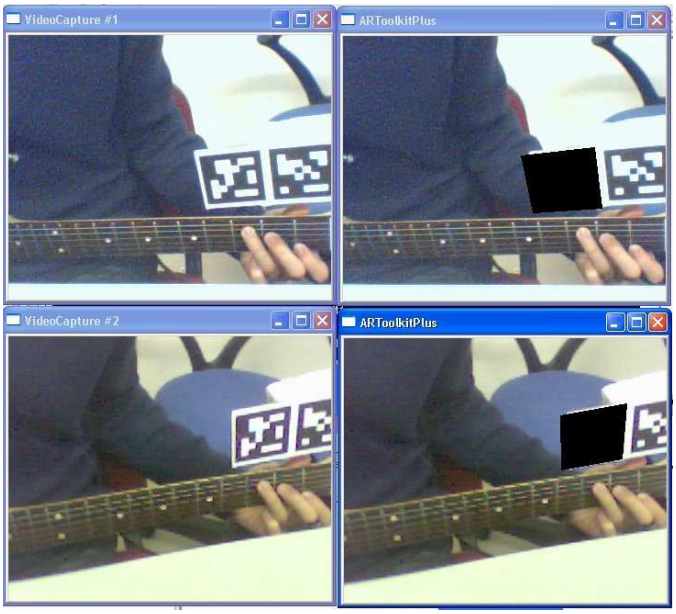

Fig. 18. Guitar tracking with ARToolkitplus

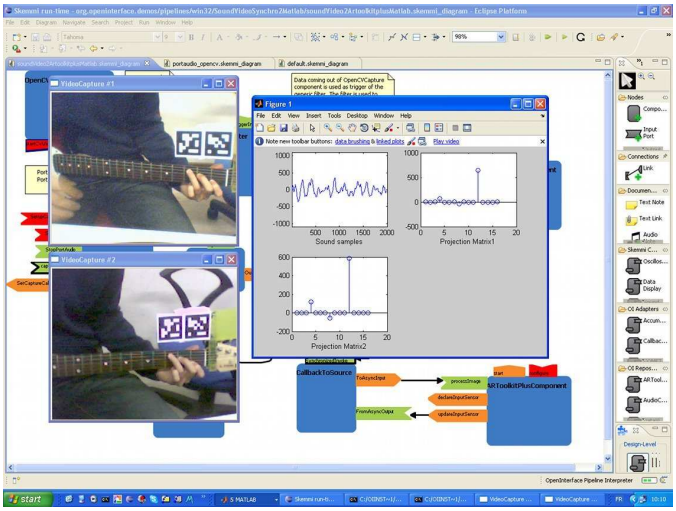

Fig. 19. Data Recording Runtime

our system will be ready, TuxGuitar will also position itself a perfect companion to Frets On Fire, complementary to the entertaining feel of the latter because the former displays the score with classical and tablature notations necessary to learn the guitar further than technique and fluidity.

The FTM library [69, 33], already available for Max/MSP and in development for PureData [75], offers a classical score visualization with the `ftm.editor` object. Once the porting in PureData is mature enough and if a guitar score visualization is added to the `ftm.editor`, this could be seen as another alternative that would be more tightly integrated into the main framework integrating modalities, PureData for the realtime version of our system.

2) Choice and modifications: We achieved initial results by creating an OpenSoundControl plugin for TuxGuitar that allows remote control through the OSC protocol, both on Matlab and patcher applications such as Pd and Max/MSP.

Currently supported commands are:

- loading a score file (`/load <file_location>`),
- initiating the playback (`/play`),
- stopping or pausing the playback (`/stop`).

We still need to modify the plugin so as to provide the visual feedback on the accuracy of the playing. Current notes to be played on the score are colored in red by default in TuxGuitar. We plan to use colors as well to label and distinguish accurately played notes (for example, in green) and wrong/missed notes (for example, in orange) and the note to be played on the score (for example, in red, the most salient color).

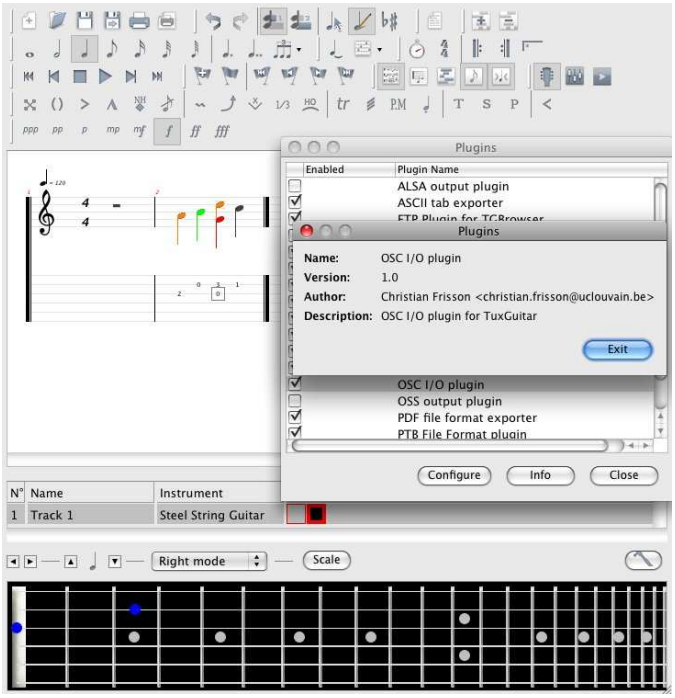

Fig. 20. Mockup of the TuxGuitar [71] interface featuring colored notes giving a visual feedback of the score following. A first version of our OSC communication plugin is also set on.

V. Conclusion and Perspectives

A. Performance Toolbox

We achieved a usable toolbox for hexaphonic or monophonic guitar. These tools are available for the Max/MSP [15] and/or PureData [59] environments. We worked on all the part of the chain of augmented music, from extraction and use of audio signal features to digital audio effects manipulated by gestural control with sensors. All the tools (Polyphonic Pitch Extraction, Fretboard Grouping, Rear-Mounted Pressure Sensors, Modal Synthesis, Infinite Sustain, Rearranging Looper, Smart Harmonizer) need to be developed for both environments (i.e Max/MSP and PureData) and documentation and/or tutorials will be provided so that everything can be freely downloadable on the eNTERFACE'09 and numediart websites and be directly usable.

Concerning the Fretboard Grouping tool, more efforts will be put in the chord / arpeggio discrimination (i.e not to base it only on the time needed to play the group). To achieve a better discrimination, one track that we will follow, will be to add time between notes directly in the group definition. Doing that, the chord / arpeggio discrimination would become obsolete as groups will not be considered anymore only as a gathering of notes but as a gathering of notes through time. A group record feature can then be added to the module so that one can record a group played in a specific way.

Physical sound synthesis sometimes lacks realism. One interesting approach can be to use pre-recorded sounds relevant to specific play on guitar such as sliding, slapping, etc.., to add more texture to the modal sounds. Since we proposed granular synthesis to enrich the guitar sustain, we could collect audio grains for enhancement of both modal sounds and sustains. By using the approach from Picard et al. [62], audio grains could be automatically extracted from recordings. In addition, the audio grains could be properly retargeted to specific outputs of sensors during runtime.

B. Study Workbench

We built a careful design of the multimodal score following system. We prototyped many algorithms for: finger tracking, guitar headstock 3D location, multiple pitch estimation from a monophonic audio signal of the guitar, bayesian networks for multimodal fusion and synchronized modalities recording (mono audio, multiple cameras). Each module works efficiently offline and separately. We build an initial synchronized recordings database.

We still need to do a proper study and working implementation of the score visualization and visual feedback of the score following. We need to test and improve the system so that it can run in real time. We also need to undertake user testing so as to evaluate and validate the precision and performance of the system. To complement the multimodal fusion, we could build an ontology of the guitar playing domain, by extracting, classifying and interpreting "guitar techniques", such as "bends", "hammer-ons", "pull-offs", "artificial harmonics", the plucking position [70].

Acknowledgment

Christian Frisson, Anderson Mills, Loïc Reboursière and Todor Todoroff are supported by numediart, a long-term research program centered on Digital Media Arts, funded by Région Wallonne, Belgium (grant N°716631).

Wen-Yang Chu is funded by the FRIA grant of FNRS, Région Wallonne, Belgium.

Otso Lähdeoja's work is partially funded by Anne Sedes from CICM, University of Paris 8.

Cécile Picard work is partially funded by Eden Games, and ATARI Game Studio in Lyon, France.

Ao Shen is supported and funded by his supervisor Neil Cooke and EECE Department, University of Birmingham.

We would like to thank Ashia Cont (IRCAM) for having provided us the source codes for the `transcribe~` flext object (C++) [12] and the related template training (Matlab). We are grateful to Damien Tardieu (FPMs/TCTS) for having

helped us modify the aforementioned code to adapt it to the guitar.

We offer thanks to Emmanuel Vincent and Anssi Klapuri who provided us their implementation of the polyphonic pitch estimation.

We show our appreciation to Jean-Yves Lionel Lawson (UCL-TELE) for assisting building the recording and integrated OpenInterface system of the "edutainment" part.

We would like to thank Otso Lähdeoja, Anne Sedes and the organizing team from CICM, for having welcomed us at Identités de la Guitare Electrique - Journées d'étude interdisciplinaires à la Maison des Sciences de l'Homme Paris Nord, on May 18-19 2009, to present the objectives of the Multimodal Guitar project. A publication on the proceedings will follow [22].

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BIOGRAPHIES

Christian Frisson received his M. Eng. degree in Acoustics and Metrology from Ecole Nationale Supérieure d'Ingénieurs du Mans (ENSIM) at Université du Maine, France, in 2005. He graduated a M. Sc. specialized in "Art, Science, Technology (AST)" from Institut National Polytechnique de Grenoble (INPG) and the Association for the Creation and Research on Expression Tools (ACROE), France, in 2006; for which he visited the Music Technology Department of McGill University, Montreal, Canada. Since October 2006, he has been a PhD student at the Communication and Remote Sensing Lab (TELE) of Université de Louvain (UCL), Belgium.

Besides playing the guitar, he participated during his MEng studies to the development of a workbench aiding luthiers to design acoustic guitars with acoustical modal analysis [24].

Web: http://www.tele.ucl.ac.be/view-people.php?name=Christian.Frisson
Email: christian.frisson@uclouvain.be

Loïc Reboursière obtained his MArts in digital scenography and audiovisual design in Valenciennes in 2008. He has been blending for several years digital arts technologies with artistic performances, what he is now pursuing at the TCTS lab from the Polytechnic Faculty of Mons. He created and interpreted a performance for spatialized hexaphonic guitar in 2008 [67].
Web: http://lilacwine.free.fr
Email: loic.reboursiere@gmail.com

Wen-Yang Chu received the B.S. degree in electronic engineering from Fu Jen Catholic University, Taipei, Taiwan in 2004, and the M.S. degrees in information and communication technologies from Universitat Politécnica de Catalunya and Université catholique de Louvain(UCL) (MERIT-Erasmus Munds) in 2008. He currently is pursuing the Ph.D degree in Communication and Remote Sensing Lab (TELE), UCL, funded by the FRIA grant of FNRS, Région Wallonne, Belgium. His research interests include adaptive mapping, educational applications, multimodal signal processing and fusion, human-computer interaction, and digital interactive arts.
Web: http://www.tele.ucl.ac.be/view-people.php?name=Wen-Yang.Chu
Email: wen-yang.chu@uclouvain.be

Otso Lähdeoja is a Finnish guitarist, composer and music researcher [42]. He obtained Bachelors and Masters degrees in Music and Musicology from University of Paris 8. He is currently working on a PhD at Paris 8 University on augmented instruments.

As a musician and bandleader, he participates in a number of musical projects, playing frequently in France and abroad.
Web: http://www.myspace.com/maamusique

John Anderson Mills holds a Computer Engineering degree (1992) from Clemson University (USA). He received his master's degree (1997) from The Pennsylvania State University in Acoustics with a thesis on noise prediction for jet engines. He received a doctorate (2008 from The University of Texas in Electrical Engineering with a dissertation on algorithmic analysis of electroacoustic music using psychoacoustic models. He joined numediart at the TCTS lab in 2009 with current interests in sound analysis, computer music, social DSP, and musician-instrument interaction.
Web: http://academic.konfuzo.net
Email: nodog@konfuzo.net

Cécile Picard is currently a Computer Graphics Ph.D. candidate at INRIA, France, in the REVES team. After receiving her diploma in Mechanical Engineering with specialization in Acoustics in 2005 at the Université de Technologie de Compiègne (UTC), France , she continued in the domain of sound and obtained in 2006 a Msc. in Sound and Vibrations at the Chalmers University in Goteborg, Sweden.

Her current research focuses on real-time sound rendering for virtual reality and in particular, on the synthesis of sounds resulting from physical interactions of various objects in a 3D virtual environment. The main goal is to address different techniques for sound rendering based on the constraints that sounds are highly dynamic and vary depending on the interaction type and objects.
Web: http://www-sop.inria.fr/reves/Cecile.Picard/
Email: cecile.picard@sophia.inria.fr

Ao Shen has a bachelor's degree in Communication Science & Engineering at Fudan University, Shanghai, China and a bachelor's degree in Electronic Communication Engineering at Birmingham University, UK. He is experienced in coding mobile application and won the second prize in Vodafone Betavine Student Competition. Now he is doing his second year of PhD study in Electronic Electrical & Computer Engineering Department, University of Birmingham.

His main interests are noise-robust multimodal system, semantic level application and fusion scheme for multimodal system.
Email: shenany@gmail.com

Todor Todoroff holds an Electrical Engineering degree from the Université Libre de Bruxelles (1987), a First Prize (1993) and a Higher Diploma (1996) in Electroacoustic Composition from the Royal Conservatories of Music in Brussels and Mons.

After doing research in speech processing at the ULB, he led between 1992 and 1997 a computer music research project at the FPMs. He pursued at ARTeM (Art, Recherche, technologie et Musique, Brussels) the development of real-time software tools for transformation and spatialisation of sounds as well as the conception of interactive systems for sound installations and dance performances.

His music has been played in many concerts and festivals around the world and he received the Prize of the Audience at the Noroit Competition (France, 91), was finalist at the Luigi Russolo Competition (Italy, 1992), CIMESP (Brazil, 1995) and Musica Nova (Czekia, 2000) and received Mentions (2002, 2005 and 2009) and First Prize (2007) at the International Bourges Competitions.
Email: todor.todoroff@skynet.be

Bacteria Hunt: A multimodal, multiparadigm BCI game

C. Mühl (1), H. Gürkök (1), D. Plass-Oude Bos (1), M. E. Thurlings (2,3), L. Scherffig (4), M. Duvinage (5), A. A. Elbakyan (6), S. Kang (7), M. Poel (1), D. Heylen (1)

(1) University of Twente, The Netherlands, (2) TNO Human Factors, The Netherlands, (3) Utrecht University, The Netherlands, (4) Academy of Media Arts Cologne, Germany, (5) Faculté Polytechnique de Mons, Belgium, (6) Kazakh National Technical University, Kazakhstan, (7) Gwangju Institute of Science and Technology, South Korea

Abstract—Brain-Computer Interfaces (BCIs) allow users to control applications by brain activity. Among their possible applications for non-disabled people, games are promising candidates. BCIs can enrich game play by the mental and affective state information they contain. During the eNTERFACE'09 workshop we developed the Bacteria Hunt game which can be played by keyboard and BCI, using SSVEP and relative alpha power. We conducted experiments in order to investigate what difference positive vs. negative neurofeedback would have on subjects' relaxation states and how well the different BCI paradigms can be used together. We observed no significant difference in mean alpha band power, thus relaxation, and in user experience between the games applying positive and negative feedback. We also found that alpha power before SSVEP stimulation was significantly higher than alpha power during SSVEP stimulation indicating that there is some interference between the two BCI paradigms.

Index Terms—brain-computer interfaces, computer games, multimodal interaction.

1 Introduction

The study of Brain-Computer Interfaces (BCI) is a multidisciplinary field which combines engineering, cognitive neuroscience, psychology, machine learning, human-computer interaction and others. Applications using this direct communication channel from brain to machine are just as diverse, from rehabilitation to affective computing.

With methods like electroencephalography (EEG) it is possible to measure voltage differences over the scalp, which are the result of brain activity in the neocortex. With this method neuroscience has identified several patterns of activity that are associated with distinct cognitive functions. EEG opens therefore a window into the mind, which can be used for a direct communication between brain and computer [17]. It has a number of advantages over other methods, as it is non-invasive, has a high temporal resolution, does not require a laboratory setting, is relatively cheap, and it is even possible to create wireless EEG head-sets. Downsides of EEG are a low spatial resolution and its sensitivity to noise and artifacts [28]. The hardware also requires some time to set up, and afterwards everything needs to be cleaned. Dry caps which do not need conductive gel and are just as easy to set up as head phones are in development, which will solve this problem.

Where originally BCI research has been focused on paralyzed patients, new developments as affordable and wireless dry cap technology make BCI viable for healthy users. Besides the novelty factor, and the magic of being able to use your brain directly for control, BCI also provides private, hands-free interaction. It increases the information users can provide applications, and applications in turn can react more appropriately, for example by also taking the user's mental state into account.

A large potential target group are gamers, as games are an area where novelty is appreciated

and learning new skills is often part of the challenge [19]. For research with patients, games can be a very interesting option as well. Virtual worlds can provide a safe environment to learn to produce specific brain activity: Accidentally steering your wheel chair off the stairs is less painful in a virtual environment. Additionally, the game element can keep tedious training fun and motivating.

Unfortunately, there are still issues that cause problems when trying to use a BCI. There are large differences between the brain activity between people, and even within one person the brain activity changes quite quickly over time [5]. This makes it difficult to create a system that will understand what the user is trying to do, especially for a longer duration. Depending on the BCI paradigm used a lot of training may be required (ranging from minutes to months), for the user to be able to generate the correct signal for the system. Alternatively, the system may be trained with user specific data to recognize the user's brain activity associated with a certain (mental) action. However, it is possible that the person trying to use the system falls into the category of the so-called BCI illiterate like 20% of the population [20]. This means that this particular user may not be able to generate the signal in a way that is measurable to the system, and hence will not be able to control it. As a result from using EEG as a measurement method, the recorded brain activity has a low signal-to-noise ratio and is susceptible to artifacts stemming from eye or muscle movements. These problems cause a high level of uncertainty when analyzing and interpreting brain signals. There are also issues with speed and timing, as relevant brain activity needs to be induced, recorded, analyzed, and interpreted, before the corresponding action can be performed in the application.

Although paralyzed patients for which BCI is the only interaction modality left may be willing to accept resulting problems with robustness and speed, healthy subjects will be less forgiving. For them many other input modalities are available. Therefore, now other more traditional usability and user experience challenges have to be solved as well, in order to exploit the full potential of this innovative technology and increase its acceptance among the general population.

Current BCI research applications are often very limited, restricting themselves to the use of one modality (BCI) and one BCI paradigm, to control one type of interaction in a very simplified game [22]. It is a big step from this situation to interaction found in current commercial video games. Besides the large amount of actions that can be taken in game worlds nowadays, gamers will not behave according to the restrictions often applied in current BCI research in order to reduce artifacts in EEG. Gamers will move, multi-task, and use multiple interaction modalities. Because of the problems with BCI at the moment, applying BCI in combination with traditional control modalities enables the use of its advantages, while its downsides can be avoided by other modes of input. The same is true for the use of multiple BCI paradigms.

The goal of this project has been the development of a game that combines traditional game control (e.g. mouse or keyboard) with BCI. This game is a platform for the study of the use of BCI in a game environment, to learn more about the situations mentioned above: using BCI in an efficient and natural way considering usability and user experience, using it in combination with other modalities, using multiple BCI paradigms within one application, allowing for a realistic setting, and possible multiplayer interaction. Besides these specific interests, this platform can also help in yielding new insights into more general issues of applying BCI.

To explore some of these previous issues, an experiment has been conducted using a multimodal, multiparadigm, single-player variety of the game. This functions also an illustration of how this platform can be used for such research. This investigation is focused on one hand on the influence of using a certain BCI paradigm on the user experience, and on the other hand on possible interference effects of using two BCI paradigms simultaneously.

Applying neurophysiological input in games gives rise to specific considerations in the design space. Hence, to start off, this new game design space for BCI is clarified in Section 2.

The third section provides more information on those BCI paradigms that were initially thought suitable for game control, considering the zero amount of training they required and the different types of input they could be applied to. Pilot studies were run to explore the most appropriate paradigm and parameters for the game. The full system consisting of the game and the pipeline for BCI control has been designed according to our specific requirements, as described in Section 4. This is followed by Section 5, which focuses on the conducted experiment and the obtained results. The paper concludes with a discussion and conclusions about the design space, the developed research platform, and the results of the conducted experiment.

2 A BCI Game Design Space

During the last decade, computer games have received increased attention from the scientific community. The academic field of *game studies*, while still in formation, already has given birth to a number of conferences and journals and the design of computer games is taught at universities around the world. These developments created techniques that may support the design of computer games and terminologies that may standardize the description and analysis of games and game design efforts. Within the project, game studies terminology was used to create a coherent description of what forms of BCI are possible in different forms of computer gaming. This "BCI game design space" first of all was needed to enable a precise definition of the couplings of neurophysiological input and game mechanics within the game and its various levels. In addition, it suggests a terminology that may be used to standardize the hitherto incoherent descriptions of these factors in BCI gaming projects.

2.1 Game studies terminology

Computer games, according to [1], consist of a *game world*, *rules* and *gameplay*. The former two comprise the entities that are present within a game as well the rules that connect these entities and define their behavior. Gameplay instead results from interaction. It emerges when a player applies the rules to the world by playing the game.

In order to be able to elicit gameplay, a coupling of the player to the game world must be established. This possibility of interaction yields a subjective experience of causal agency that results from a player's activity and its directly perceivable results in the game world. This experience has been named *effectance* [14]. While effectance is rooted in feedback on the level of in- and output, a player will also experience a game on the level of its rules: She will, for instance, not only move entities in the game world but eventually also win or loose the game. The experience of successfully interacting with a game's rules has been called the perception of *control* [14]. Both, effectance and control, are thought to be crucial factors for the induction of computer game enjoyment [14].

Computer games that not only rely on traditional forms of interaction, but that use physiological sensors pose new challenges for the definition of both: the direct application of inputs to the game world – and therewith the influence of these sensors on the level of effectance – as well as the role of the sensors for the game rules, on the level of control. Notice that neurophysiology is a part of physiology that deals with the nervous system. Therefore, while a BCI component (like an EEG sensor) is better classified as a neurophysiological one, it is also not wrong to refer to it simply as a physiological one.

2.2 Classification of BCI paradigms

A number of BCI paradigms exist and each of those may be suitable to support different forms of effectance. In the following, a two-dimensional classification of this BCI input space is suggested. While being formulated for BCI input, this classification generalizes to all forms of physiological input to computer games.

The dimensions of this classification are defined by (i) the dependence on external stimuli and (ii) the dependence on an intention to create a neural activity pattern as illustrated in Figure 1.

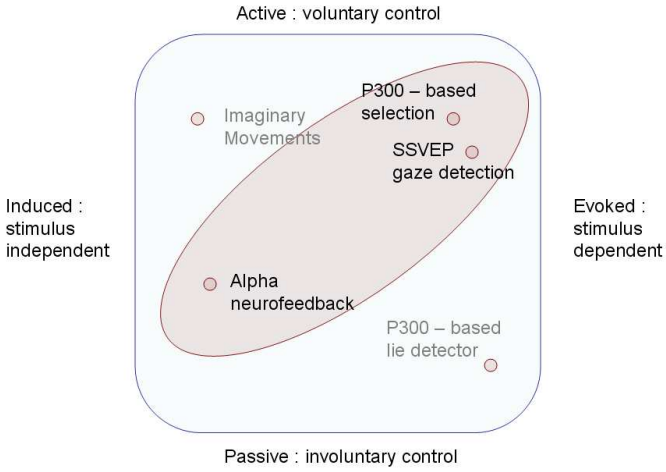


Fig. 1: A classification of BCI paradigms, spanning voluntariness vs. stimulus dependency.

Axis (i) stretches from exogenous (or evoked) to endogenous (or induced) input. The former covers all forms of BCI which necessarily presuppose an external stimulus. SSVEPs as neural correlates of stimulus frequencies, for instance, may be detected if and only if evoked by a stimulus. They hence are a clear example of exogenous input. Endogenous input instead does not presuppose an external stimulus. One prominent example is the usage of alpha band power in neurofeedback applications. While alpha activity may be influenced by external stimuli, it in principle can be measured when no stimulus is present and hence classifies as endogenous. Another way of separating both poles of the axis is the possibility of building a *self-paced* (or asynchronous) BCI [25]: Only endogenous input can be used to build a system that is self-paced, in the sense that it can decide if a user initiates an action by brain activity, whenever she does so. On the other hand, all forms of exogenous BCI necessarily are synchronous.

Axis (ii) stretches from active to passive input. Active input presupposes an intention to control brain activity while passive input does not. Imagined movements, for instance, can only be detected if subjects intend to perform these, making the paradigm a prototypical application of active BCI. Alpha and other measures of band power instead can also be measured if subjects exhibit no intention to produce it.

A summary of BCI Games by Reuderink [22] distinguishes between the application of band power feedback (F), P300, VEP and the neural correlates of imagined, planned and real movements (M). According to the scheme proposed here, all cases of F listed in [22] classify as passive-endogenous, all applications of P300 and VEP classify as active-exogenous and all cases of M classify as active-endogenous. However, other applications are possible or – outside the context of gaming – even are in use: P300 lie-detectors, for instance, classify as passive-exogenous. Using the changing VEP strength evoked by a stimulus that constantly is present as a correlate of attention would also classify as passive-exogenous.

2.3 Physiological effectance and control

If a BCI input directly affects the game world, the whole BCI feedback cycle is found on the level of effectance. In this case we speak of *direct* interaction. Direct interaction is usually associated with active BCI in which the user makes an effort to create a control signal in order to succeed at an aim. To the contrary, if not the game world but its rules are affected, parts of the interaction take place on the level of control. Here, BCI may be used to change overall parameters of the game, such as its speed or difficulty. Such forms of interaction are less directly perceived and hence can be named *indirect*. Indirect interaction is usually realized through passive BCI in which the user does not put much of his effort on using the BCI but rather on a more important control modality.

Moreover, if physiological activity does affect the game world or the rules, but if influencing these is not necessary in order to win the game, it constitutes a form of interaction that merely is *auxiliary*. An example for auxiliary interaction would be a game in which physiological activity changes the game's appearance or is used to gain bonus points. This sort of interaction is used mostly for non-critical features, and thus is very suitable to employ BCI paradigms which are hard or time consuming to detect.

2.4 Multiplayer BCI

In multi-player games the number of possibilities of affecting the game world or its rules increase: First, the game may be competitive, cooperative or generative. While computer gaming started with competitive games mostly (such as *Spacewar!* and *Pong*) in the age of online multi-player games cooperative gaming has gained much importance. Generative games are comparably rare, one prominent example is *Electroplankton* by Toshio Iwai.

Second, the mapping from physiological measurements to the game may either take place separately for each player or in conjunction. In *BrainBall* for instance, alpha band power of two players is combined to alter the position of one single ball, making it an example for conjunct control of the game [10]. Of course, it also would be possible to control the positions of two balls by one player each, creating a game using separate controls.

3 The BCI Paradigms

Existing BCI paradigms in BCI applications can be divided in several ways. The previous section distinguishes the classification into passive vs. active, and evoked vs. induced paradigms. To control an active BCI, one has to actively perform mental tasks such as motor imagery. For example by imagining left or right hand movement a cursor can be controlled to move up or down. This principle was applied in the game brainpong, where a bat is controlled to move up or down to block an approaching ball, using motor imagery [16]. Typically, active BCIs demand the most intensive user training. Evoked BCIs require probe stimuli, stimuli presented by the system. By attending to one of the stimuli, an interpretable brain signal can be elicited. In an evoked BCI this interpretation is translated into a command of the system. The type of brain signal that is elicited is dependent on the characteristics of the stimuli provided. The Steady State Visually Evoked Potential (SSVEP) and the P300 are both features in the EEG that can be elicited by certain probe stimuli and are explained in more detail later on. These features are interesting for BCI applications, because the signal-to-noise ratio is relatively high and they do not require user training. Passive BCIs detect the changes in cognitive and affective states, and do not require the user's active attention or the performance of cognitive mental tasks. In principle BCIs that belong to this category are not used for direct control (e.g. of cursor movement), but are more suitable for indirect control. Alpha band power can be used in this passive context, as it is related to a relaxed mental state [3]. However, the users can also learn to control their alpha activity, thus complicating the location of this approach along the passive/active dimension.

For the current game, it was decided to forgo paradigms that need extensive user training or machine learning, while at the same time a variety of different types of paradigms was wanted. This resulted in the selection of SSVEP, P300, and neurofeedback based on the power in the alpha band. This section describes these BCI paradigms. Two pilot studies were carried out to check the feasibility of the exogenous BCI paradigms in this game implementation, explore appropriate parameters and test classification algorithms for the BCI paradigms intended for the game control. The first study explored the neurophysiological responses to stimuli flickering with a fixed frequency (SSVEP). The second study investigated the responses to slower changing stimuli (P300). The final subsection provides information about alpha activity, based on literature.

3.1 SSVEP

SSVEPs can be induced if a person is attending to a flickering visual stimulus, such as an LED. The frequency of the attended stimulus [21], as well as its harmonics [18], can then be found in the EEG. SSVEPs are interesting for BCI-applications, because multiple stimuli can be provided simultaneously in contrast to the P300 for which stimuli have to be presented sequentially (see subsection 3.2). If the stimuli are all flickering with a different frequency, then the attended frequency will dominate over the other presented frequencies in the observers EEG. A commonly used method to detect SSVEPs is to apply a Fast Fourier

Transformation on the EEG and compare the amplitudes in the frequency bins corresponding to the frequencies of the stimuli provided. If only one stimulus is used, the amplitude of the corresponding frequency bin is compared to a set threshold. Frequencies of stimuli between 5-20 Hz elicit the highest SSVEPs [9]. SSVEPs are recorded over the visual cortex; O1, Oz and O2 according to the 10-20 system.

So SSVEPs are dependent on provided flickering stimuli, which need to flicker very constantly. The goal of this offline study was to investigate if it is possible to create such stimuli that are able to elicit the SSVEP response with Game Maker™. Furthermore, the parameters for this BCI paradigm were investigated in terms of appropriate frequency and the size, shape and pattern used for the stimulus.

3.1.1 Method

Stimuli: For the creation of visual flickering stimuli, several factors have to be taken in account. Firstly, is the bandwidth of frequencies that in principle can elicit robust SSVEPs, as mentioned above this is between 5 and 20 Hz. Secondly, in the current study it is desired that the stimuli are offered on the screen, so the possible frequencies are dependent on the screen refresh rate and characteristics. Previous experience showed that the SSVEP induction can not done reliably when the stimulus appearance is changed in every frame. At least two frames after each other need to show the same stimulus (color). Accordingly, the maximum stimulus frequency that can be obtained with a screen refresh rate of 60 Hz is 15 Hz (see Table 1). Therefore, a simple flickering stimulus is created by the alternation of two frames presenting a black stimulus and two frames presenting a white stimulus. Similarly, more complex stimuli are created, for example flickering checkerboards, which are often used to elicit SSVEPs. To investigate the robustness of the stimuli created with Game Maker™, such flickering checkerboards were presented with the frequencies 7.5, 8.57, 10, 12 and 15 Hz. To this end, one color of the stimulus was presented for two images, while the other color was presented for 2-6 images (see Table 1), resulting in four to eight images that were connected in one stimulation period.

Frames per period	Frames on (1) and off (0)	Frequency of stimulus (at 60 frames per second)
4	...1100...	15 Hz
5	...11000...	12 Hz
6	...110000...	10 Hz
7	...1100000...	8.57 Hz
8	...11000000...	7.5 Hz

TABLE 1: Possible frequencies of a flickering stimulus on a LCD with a screen refresh rate of 60 Hz are shown.

As imaginable, flickering checkerboards are visually not appealing and are annoying to look at. Therefore besides the standard checkerboard, also other shapes and appearances of stimuli were investigated. The appearance and characteristics are shown in Table 2. To limit the number of experimental sessions, the disk stimuli were only presented in one frequency, namely 12 Hz.

Experimental Setup: For this pilot study only two participants were involved. They were seated in front of a laptop, approximately 60cm in front of the screen. Each stimulus was presented for 60 seconds, and appeared in the middle of the screen. After each stimulus presentation, a pause screen appeared. For details on the recording of EEG, see Subsection 5.1. The sample frequency for this EEG recording was 2048 Hz.

Task: Participants had to sit still in front of the laptop and attend to the stimulus presented. They were instructed to blink as few as possible and to avoid any other movement completely during stimulus presentation. Participants controlled the start of each condition.

3.1.2 Results

Offline Analysis: The EEG recorded at O1, Oz and O2 was first cut out for each stimulus presentation from 40.000 until 100.000 data points after the start of the stimulus (60.000 data points recorded with a sample frequency of 2048 Hz corresponds to approximately 30 seconds). These extracted signals were first common-average referenced (CAR, see Subsection 4.2.2), and then transformed to the frequency domain with a Fast Fourier Transformation.

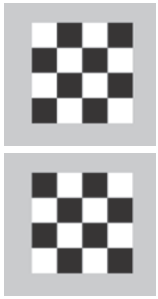
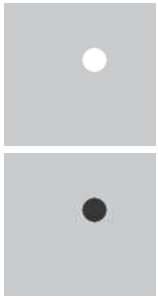
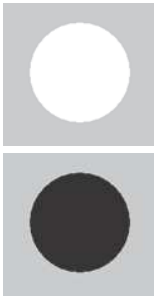
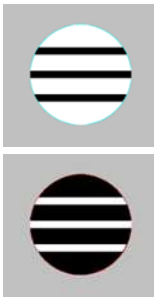
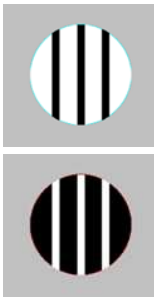
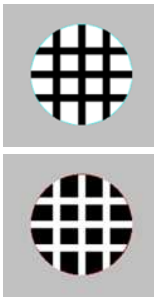
Checkerboard	Small disk	Large disk	Large disk with horizontal stripes	Large disk with vertical stripes	Large disk with horizontal and vertical stripes
					
Stimulus freq. of 0, 7.5, 8.57, 10, 12, 15Hz	12Hz	12Hz	12Hz	12Hz	12Hz
Inner diameter of 4o	1o	4o	4o	4o	4o

TABLE 2: The table shows the presented stimuli and the presentation parameters frequency and size. The images on top were altered with the bottom images to create the flickering stimuli. The third row shows the frequencies each flickering stimulus was presented with. The last row relates the size of the stimuli to the smallest, namely the small disk (o).

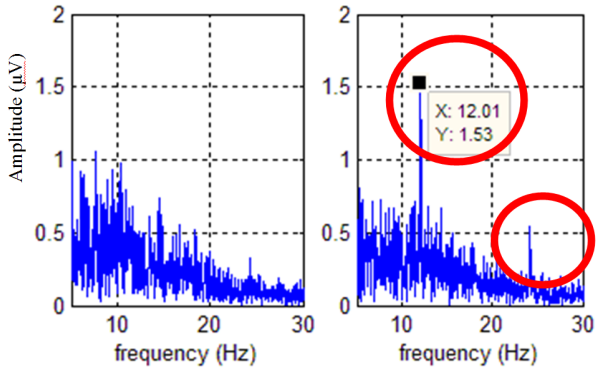


Fig. 2: The frequency spectrum of a participants EEG recorded at Oz during: no stimulus presentation (left) and checkerboard presentation of 12 Hz (right). Here the main response of the SSVEP and its first harmonic are clearly visible.

For the checkerboard stimuli, clear SSVEP responses were found in the EEG of both participants for 7.5, 8.57 and 10 Hz (see also Figure 2). In one participant also the stimuli flickering at a frequency of 12 and 15 Hz evoked SSVEP responses, although from the latter one only the second harmonics was found. From the alternative stimuli, the large disk and the large disk with horizontal and vertical stripes were able to evoke SSVEP responses in both participants. For one participant the large disk with horizontal stripes and for the other participant the large disk with vertical stripes also induced SSVEP responses. No significant differences were found for responses recorded at O1, Oz and O2.

Classification: In order to develop a BCI that uses the SSVEP paradigm, an online classification algorithm is needed. To simulate an online situation, the recording of 60 seconds was sliced into four-second windows, with steps of one second between the start of each window. After CAR and FFT is applied, the SSVEP detection consists of comparing the target frequency power to the maximum peak in the frequency bin around the target, with a size of 3 Hz. If the ratio between these two energy peaks exceeds an experimentally determined threshold of 0.8, the window was said to contain SSVEP. This SSVEP detection method is described in detail in Subsection 4.2.2, and is depicted in Figure 7.

After applying the method described above on the OZ channel the results presented in Table 3 were obtained. The table shows the true

Stimulation frequency	Checkerboard	Small disk	Large disk	Large disk with horizontal stripes	Large disk with vertical stripes	Large disk with horizontal and vertical stripes
			Subject 01			
7.5Hz	84%	-	-	-	-	-
8.57Hz	93%	-	-	-	-	-
10Hz	98%	-	-	-	-	-
12Hz	90%	56%	92%	79%	76%	97%
15Hz	90%	-	-	-	-	-
			Subject 02			
7.5Hz	87%	-	-	-	-	-
8.57Hz	68%	-	-	-	-	-
10Hz	82%	-	-	-	-	-
12Hz	52%	44%	84%	48%	63%	73%
15Hz	80%	-	-	-	-	-

TABLE 3: The true detection rates of SSVEPs for the different stimuli. The perfect rate is 100 % in the data used here.

detection rates (the recognition of SSVEP during actual SSVEP stimulation) for the different objects and stimulation frequencies. Please note that the optimal performance is 100%, as the true detection rate was calculated only on data with the stimulation present.

Assuming that the ability of the stimulus to elicit SSVEP is the main reason for the obtained true detection rates, those stimuli that yielded the best results qualify for further exploration. The stimuli that resulted in a good classification result for both subjects were:

- Checkerboard pattern flickering at frequencies of 7.5, 10 and 15 Hz
- Large disk and the large disk with both vertical and horizontal stripes, flickering at a frequency of 12 Hz

From these the checkerboard at 7.5 Hz and the large disk at 12 Hz were selected for further evaluation. The large disk was selected because it seemed less obtrusive than a flickering checkerboard, which is relevant for application in the game. The checkerboard flickering at 7.5Hz was selected for further analysis because of the potential interferences of the frequencies from 8 to 12 Hz with the other BCI paradigm used in the game. At all frequencies, except 7.5 and 15 Hz, the SSVEP would be in the alpha frequency range used in the game for the neurofeedback BCI paradigm. Between the true detection rates for 7.5 Hz and 15 Hz stimulation only a minor difference was observed.

For these selected stimuli, the optimal window length was explored. For this, for each window duration, besides the true detection rates, also the false detection rates (detection of the stimulus when no stimulus was presented) and the classification accuracies (total number of correct classifications divided by the total number of classifications) were calculated. The results are presented in Figure 3. As expected, the classification accuracy improves with longer window durations, as it contains more data. The figure shows that windows of at least 3 seconds are required to obtain proper classification results. For shorter windows the true detection rate is still high, but the false detection rates increase dramatically, decreasing the classification accuracies to below 70%.

3.1.3 Conclusion

The offline analysis of EEG recorded while attending to flickering stimuli created with Game Maker™, shows that SSVEPs can be elicited with these stimuli. The offline analysis and the offline classification both showed well detectable SSVEPs for both subjects for the stimuli: checkerboards flickering at 7.5, 10, and 15 Hz, and the plain large disk and large disk with both horizontal and vertical stripes flickering at 12 Hz. Of these stimuli, the plain large disk is thought to be the least obtrusive, and therefore is implemented in the game. The developed classification algorithm seems to be robust enough for implementation in an online classification structure. Analysis showed that

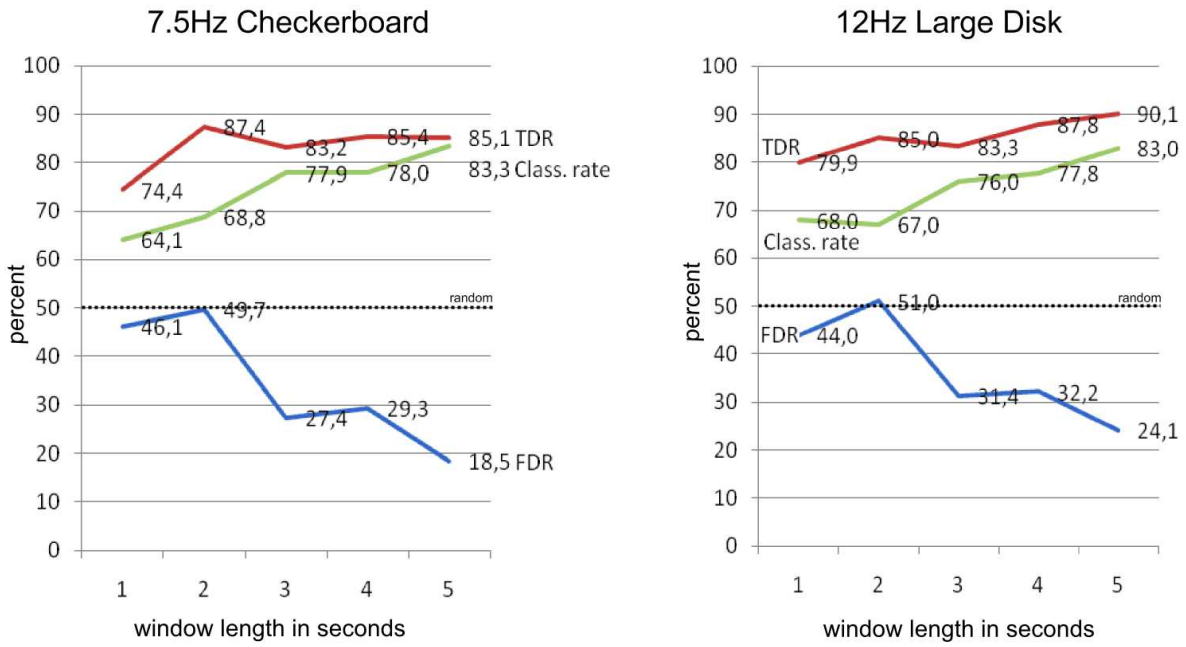


Fig. 3: The classification accuracy, true and false detection rates for the checkerboard and large disk stimuli flickering at 7.5 and 12 Hz, respectively.

windows of at least 3 seconds are required. So the game requires the user to focus for at least 3 seconds at flickering stimuli if presented.

3.2 P300

A P300 is an event-related potential (ERP). The P300 (also referred to as the P3) is a positive peak in the EEG that occurs approximately 300ms after the presentation of a *target* stimulus that stands out from other *standard* stimuli or *distractors*. One reason why the stimulus stands out can be due to differences in appearance, e.g. when one black sheep is presented after ten white ones. The experimental paradigm is called an oddball paradigm [12]. The P300 amplitude decreases if the target and stimuli are more similar [6]. Another reason is because a person is attending to a certain stimulus. The P300 is thought to be related to a higher level attentional process or orienting response. In general P300s are detected at Fz, Cz and Pz as defined by the 10-20 system. To elicit a P300, probe stimuli can be presented in the visual, auditory and tactile modality [2].

The first BCI application that used the P300 paradigm is the P300-matrix speller [8]. In this application letter and numbers are placed in a 6 by 6 matrix. The rows and columns flash up sequentially. Every time the symbol of one's choice flashes up and the user is attending to it, a P300 is (potentially) elicited. In this way, users (e.g. patients with neuromuscular diseases) can spell words and communicate with their environment, although very slowly (approximately 1-2 words per minute). As the P300 can be easily modulated with attention, it is an interesting component to use in games.

To test the feasibility of using P300 within a game, an offline experiment has been conducted that tested visual stimuli created in Game Maker™. The stimuli were shaped like bacteria, testing the potential applicability of such a stimulus in a game. Additionally, the possibilities to let a stimulus stand out (instead of flashing up) were investigated by changing stimulus' color, size and angle.

3.2.1 Methods

Experimental Setup: The general setup was similar to the previous pilot experiment (see Subsection 3.1). Comparable to the spelling matrix, stimuli are grouped, similar to rows and columns. However, visually, the positioning of

the stimuli is unstructured, to simulate a game situation. At the start of each trial in this offline experiment, a target stimulus was indicated. Each group was highlighted for 150 ms followed by an inter-stimulus interval of 150ms. The presentation of the groups was done in random order and repeated nine times.

Stimuli: Three different possibilities to let a stimulus stand out were tested. See Table 4 for the visuals.

Task: A target was indicated at the start of each trial, by highlighting it for 2 seconds. The participants were instructed to count the number of times this particular target stimulus was changed, to keep their attention focused on the target. Furthermore they were instructed to sit still, move and blink as few as possible.

Analysis: The P300 potentials were analyzed by averaging the signal of a certain electrode (the most important ones were Cz and Pz) that was recorded from 200 ms before until 800 ms after the stimulus-onset. The signals were baseline-corrected by the subtraction of the average of the 200 ms before stimulus-onset. After that the signals that were related to the target-stimuli were averaged (two signals per trial), and the signals that were related to the non-target-stimuli were averaged (four signals per trial).

3.2.2 Results

The results of the analysis for EEG responses and also the average over the nine trials are shown in the graph below (see Figure 4). The graph shows the P300 elicited by the stimuli that changed color (orange stimuli were neutral and black stimuli were highlighted), as a highlight-effect. The other conditions used, 'change size' and 'rotation', also elicited P300s. However they were lower in amplitude.

3.2.3 Conclusion

Based on this offline analyses, it is expected that the P300 paradigm may be usefull in the game, and good results can be expected if at least two trials are used. This would require 3.6 seconds of data before a classification can be done. The highlight effect that gave the best results was changing the color of the stimulus from orange to black. Unfortunately there was not enough time during the eNTERFACE workshop to also complete the online P300-pipeline. Therefore this is recommended for future work.

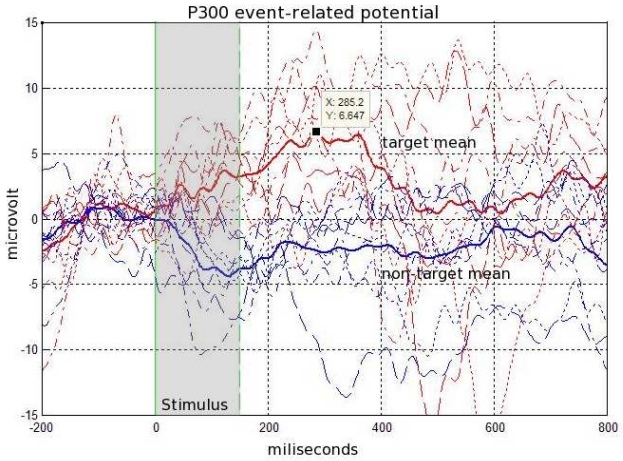


Fig. 4: EEG response of one participant to target stimuli (red) and non-target stimuli (blue) recorded at Cz. The stimulus was present during the grey area. The two thick lines represent the averages over nine trials: the EEG response to targets is clearly different from the response to non-targets. The averaged target line shows a peak at 285 ms after stimulus onset, indicating the presence of a P300.

3.3 Alpha

The term 'alpha rhythm' is restricted to brain activity in the alpha range occurring at the back of the head, which is related to a relaxed wakefulness and best recorded with eyes closed, according to the definition of the International Federation of Societies for Electroencephalography and Clinical Neurophysiology [4]. In our report, alpha band power is used in the more general sense of energy in the frequency band of the alpha rhythm: 8 to 12 Hz, which can be observed over all cortical regions.

Alpha activity used to be considered to be inversely related to neuronal activity. This can be interpreted either as cortical inhibition, or cortical idling. This view is shifting, as alpha is now seen to have functional correlates to movement and memory [26].

As a correlate to relaxed wakefulness, alpha activity could be an interesting measure for passive BCIs. Alpha activity is also considered an important tool in neurofeedback. Besides

Standard stimulus	Size change	Color change	Rotation
			

TABLE 4: The stimuli for the P300 paradigm. The standard stimulus, and the changes in size, color, and rotation used to elicit the P300.

helping patients, it might also be used to improve our mental capabilities, as research has indicated relations between alpha activity and intelligence [7], and the ability to cope with stress [27]. This is another reason why alpha neurofeedback and neurofeedback in general could be interesting BCI paradigms to use in games.

3.4 Conclusions

For this project, three potential paradigms were looked into, which were selected based on their characteristics and the minimal amount of user training and machine learning they required. These paradigms were looked up in literature, and for the two evoked paradigms small pilot studies have been conducted.

SSVEPs can be elicited with a stimulus looking like a plain large disk, which is considered to be less obtrusive then for example the checkerboard stimulus often used for this paradigm. Although this disk was only tested at 12 Hz, the frequencies of 7.5 and 15 Hz obtained good results for the checkerboard stimuli. To minimize interference with the alpha frequency range used in the neurofeedback paradigm, the flickering of the disk with 7.5 Hz seemed a good stimulus choice for the SSVEP paradigm. To obtain an acceptable accuracy of detection, windows of at least three seconds are recommended.

Alpha could be an interesting correlate for the mental state of relaxed wakefulness, to be used as a passive BCI modality, or in a more active way with potential mental benefits as a result of the training.

For P300, the highlight effect of changing the color of the stimulus from orange to black gave the best results. At least two trials would be recommended for classification, which would require 3.6 seconds of data. An online pipeline for this paradigm has not been implemented during this workshop, but is recommended as future work.

4 The Game and BCI Design

The application was built in guidance of principles and requirements defined in §4.1.1 and §4.2.1. For the ease of maintainability and optimal performance the system was decomposed into subsystems, namely the game and the data processing. The game subsystem is responsible for running the game and sending the markers depending on the input received from EEG analysis results and other traditional modalities. On the other hand, the data processing subsystem returns to the game the results it computed according to the markers and the EEG signals received. The overview of the system architecture can be seen in Figure 5.

4.1 The Game

This subsection describes how the game world, game levels and game rules are implemented in accordance to the requirements defined.

4.1.1 Requirements

1. Scientific: The game is intended to be a basis for investigation of (1.1) the possibility of combining BCI with conventional controls and (1.2) the possibility of using multiple

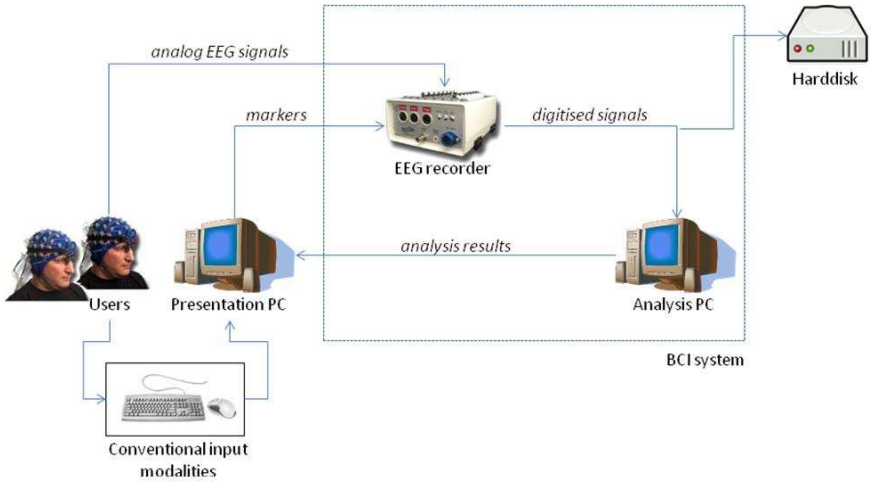


Fig. 5: Overview of the system architecture.

BCI paradigms. In addition, (1.3) it should be possible to easily extend the game with multiplayer functionality.

2. *Usability*: The game should be easy to understand and uncomplicated in use, and thus (2.1) be playable without training. In order to elicit subjective perception of control, (2.2) the game should provide persistent visual information indicating progress in terms of its rules. Finally, if players are meant to perceive causal agency based on neurophysiological recordings, (2.3) the game must provide direct feedback on the neurophysiological inputs used.

The game should equally fulfill both scientific and usability requirements.

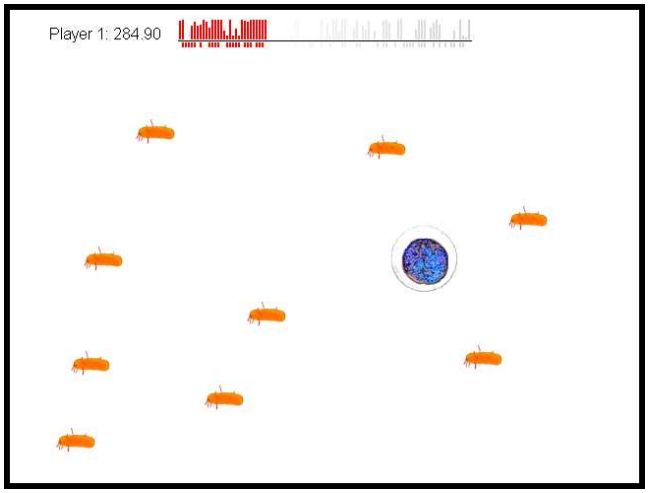


Fig. 6: The game world. Nine targets (orange "bacteria") and one player (blue "amoeba") are present. The player's score is shown at the top left. The histogram above the line depicts her recent alpha band power, below the line the SSVEP classification results are marked.

4.1.2 Game world

The game was built using the Game Maker™ development platform. The game world consists of a small number of entities: player avatar(s) (the amoeba), targets (bacteria), a numeric representation of the points obtained so far, a graph depicting the recent history of alpha band power and SSVEP classification and SSVEP stimulus (which always is associated with one of the target items) when it is triggered. The numeric representation of points functions as a high-level indicator of progress in terms of the game rules (req. 2.2) while the graph depicting alpha band power and SSVEP classification results functions as a low-level indicator of the neurophysiological coupling of the player and the game (req. 2.3).

4.1.3 Game levels

The game comprises various levels, each using the same game world but slightly differing in terms of rules. The levels *Keyboard only* (*K*), *Keyboard+Alpha* (*KA*) and *Keyboard+Alpha+SSVEP*

(*KAS*) have been implemented and tested. Furthermore, a *Keyboard+Alpha+P300* (*KAP*) level has been realized, but not tested. The decision to use alpha band power, SSVEP and P300 was guided by the requirement that it should be possible to play the game without training (req. 2.1). Imagined movements, for instance, presuppose a training phase and thus would violate this requirement. The decision to combine alpha band power with SSVEPs or P300 respectively was taken because it should be possible to analyze the combination (and possible interactions) of multiple BCI paradigms in one game (req. 1.2).

4.1.4 Game rules

Some general rules are the same for all levels, others vary with the specific level which will be explained in this subsection.

General rules: The game world always contains nine target items, which never may overlap. If the distance d between the center of a player avatar and a that of a target is below the radius of d_{min}, the target can be "eaten". Eaten targets disappear and are replaced by a new target, randomly placed on a free spot on screen. Thus, visual disappearance of target items, in addition to the numeric display of score, indicates the progress in terms of game rules (req. 2.2). Target successfully eaten results in points for the player. Eating failures result in negative points. The rules for eating are defined differently in each level. The ultimate goal of the game is to obtain as much points as possible.

Movement is performed using the keys, resulting in direct feedback through changed avatar position. Avatar position also jitters by some random noise and the effect of pressing a key depends on some external values, i.e. game controllability varies. Since the influence of key presses on the position is variable, the change of position per key press also provides direct feedback on how the player currently affects game controllability. If controllability is affected by neurophysiological measures (as in *KA*, *KAS*, and *KAP*), this implies that the feedback provided is direct feedback on neurophysiological activity (req. 2.3). In addition, by affecting controllability with neurophysiological measures, keyboard input (a conventional control) is combined with neurophysiological input (req. 1.1).

Let x and y denote a player avatar's position, s its speed , $c \in [0,1]$ the external factor determining controllability and $random(x)$ a function that returns a real value from $[1,x]$. Pressing the "right" key results in the following calculation:

$$x_{new} = x_{old} + (s + (random(s) - \frac{s}{2})) \times c$$

$$y_{new} = y_{old} + (random(s) - \frac{s}{2}) \times c$$

In addition, even if no key is pressed, the avatar position changes from frame f to frame $f+1$ as follows:

$$x_{f+1} = x_f + (random(s) - \frac{s}{2}) \times c$$

$$y_{f+1} = y_f + (random(s) - \frac{s}{2}) \times c$$

Level K rules: This level uses no EEG data at all. Hence the factor c is set to a random value in $[0.4, 0.6]$. In this way controllability will vary but stay within a range from which large deviations of controllability are possible for the other levels. Eating is triggered by pressing a key. It is a success if the nearest target meets the distance condition described above ($d \leq d_{min}$). Points p are calculated by:

$$p = 100 \times (1 - \frac{d}{d_{min}})$$

If the eating attempt is triggered while the distance is above the threshold, p is assigned to -50.

Level KA rules: Eating is performed and evaluated as in level *K*. However, c is linked to the player's relative alpha band power ($\alpha \in [0,1]$). In a pilot study, relative alpha power was found to be in $[0.15, 0.23]$ for most subjects. Thus, an *ad hoc* scaling $[0.15, 0.23] \rightarrow [0,1]$ was introduced, creating a scaled α_s. For future versions of the game, subject dependent scaling

methods or adaptive scaling are to be considered.

$$\alpha_s = \frac{(\alpha - 0.15)}{0.08}$$
$$c = \alpha_s$$

Therefore, controllability is to be affected by the player's mental state, while the influence on controllability is visualized by the jitter exhibited by the avatar (req. 2.2) and both keyboard and BCI input are combined (req. 1.1).

Level KAS rules: The factor c is linked to alpha band power as in level *KA*. The process of eating is changed as follows: approaching a target closer than the eating distance d_{min} triggers a SSVEP stimulus appearing next to the target. The association of stimulus and target is visualized by a line connecting both. The stimulus consists of a circle with a diameter of 64 pixels and flickers with a frequency of 7.5 Hz, changing from black to white. It is displayed for 6 seconds on the screen. Between the seconds $3-6$, SSVEP classification results are recorded (this specific interval depends on the window size of 4 seconds used in the analysis pipeline). If the mean output of the classifier is above 0.5, the target gets eaten. Points are calculated using the mean alpha power measured between the seconds $3-6$.

$$p = 100 \times mean(\alpha_s)$$

Thus, for players, it is of benefit to control both alpha band power and SSVEP simultaneously (req. 1.3). If SSVEP classification fails, -50 points are given, the target "escapes" and is moved away from its current position.

Level KAP rules: Instead of triggering a SSVEP stimulus, approaching a target now triggers repeated highlighting of groups of targets. To do so, the nine targets on screen are organized in six groups. Each group consists of three targets and each target is part of two groups. Groups are highlighted by replacing the image of its member objects by a bigger version of the same image for $150ms$. Between each flash, an inter-stimulus interval of $150ms$ is used. After each group has flashed once, a P300 response for the selected target is measured and, if classified correctly, the target is eaten successfully. Again, alpha activity during that process is used to scale points received for eating. If no target or a non-target is classified using P300, the target escapes.

4.1.5 Effectance and control

On the level of effectance, players interact with the game world by controlling their avatar's position using the keys. In addition, they control eating and target "escape" behavior by focusing SSVEP or P300 stimuli (in an exogenous-active condition).

On the level of control, players change the game rules based on their alpha band power: a high alpha is to enhance the controllability of the game using keys (in an endogenous-passive condition).

4.1.6 Single- and multi-player

The initial prototype of the game is single-player only. But in principle it can easily be scaled to larger number of players (req. 1.3). In a *competitive* mode, players compete for points. In a *cooperative* mode, players try to clear a level from all targets as soon as possible. Both modes employ separate BCI control. Other ways of cooperative game play are planned, such as a mode in which player avatars are merged for conjunct control.

4.2 Data acquisition and processing

This subsection defines the requirements and steps for data acquisition and processing.

4.2.1 Requirements

1. Hardware considerations: The EEG signals should to be acquired by the BioSemi ActiveTwo system. For this purpose, the game should run on a computer with a parallel port to be able to send the signals and markers. The game and analysis pipeline should be able to communicate with each other via TCP. The computer running the game should possess a monitor with a resolution of 1024x768 and a minimum refresh rate of 60 Hz to be able to correctly display the SSVEP frequency. The analysis pipeline should be able to receive

the signals from the ActiveTwo system via USB. BioSemi active electrodes should be used in measurements as advised by the BioSemi company.

2. *Performance*: The time lag between the analysis pipeline, game engine, and ActiveTwo system should be kept at minimum for the sake of analysis accuracy and game amusement. Both the gaming and pipeline computers should be fast enough to run continuously, without any halts or delays.

3. *Physical environment*: All the equipment should be operated, preferably, in a room free of electrical noise. Users should be able to access the gaming computer but better be kept away from the analysis computer to avoid distraction.

4.2.2 Design

For signal processing and machine learning purposes, Golem and Psychic libraries by Boris Reuderink were employed in the pipeline [23], [24]. The EEG signals are continuously read as overlapping 4-second-sliding-windows, the interval between window onsets being 1 second. The steps for processing a window is displayed in Figure 7. Brain potentials have to be measured with respect to a reference. This reference can be based on some electrodes (e.g. placed on ear lobes or mastoids) but also be electrode-free by re-referencing, i.e. the reference potential is created from a computation based on a set of electrodes. Common average referencing (CAR) is such a spatial filter used for re-referencing. It consists of computing the mean of the whole set of electrodes per sample and then subtracting it from each EEG channel. It was shown to be superior to the ear-reference and other re-referencing methods [15]. Therefore a data window is first re-referenced by CAR.

Regarding the relative alpha power computation, the data in channel Fz was extracted from the window. Applying fast Fourier transform (FFT) on the data the power within the alpha band [8 Hz, 12 Hz] was calculated and divided by the total power within the frequencies [4 Hz, 40 Hz].

For the detection of SSVEP presence, the data in channel O2 was extracted from the window. Channel O2 was used since no significant difference was found in the response recorded at O1, Oz and O2 (see §3.1) and during experiments recording sites O1 and Oz were problematic. Then the power in the frequency domain was computed by FFT. The power spectrum is expected to contain a peak at the flickering frequency of the circle object on the screen. The flickering frequency ($f_{flicker}$) of 7.5 Hz was used as it was one of the best performing frequencies (see §3.1) and does not interfere with the alpha band. But detection of this peak is a bit tricky task. Sometimes the amplitude of the flickering frequency may not be present in the spectrum but, instead, in the frequencies that are close to it. It can still be approximated by increasing the resolution of FFT, or calculated from known values for neighboring frequencies, but result can be inaccurate. Another point is that the flickering frequency may be unstable on custom computers and LC displays. Therefore, SSVEP in some cases might not be detected correctly. Taking all these challenges into consideration, following procedure was defined for detecting the peaks in the spectrum:

1) Look for the frequency with the maximal amplitude (f_{max}) between the range of [$f_{flicker}$ - 1.5 Hz, $f_{flicker}$ + 1.5 Hz].
2) If $f_{flicker}$ is not represented in the spectrum obtained by FFT, look for the nearest represented frequency ($f_{nearest}$) and set $amp(f_{flicker}) = amp(f_{nearest})$.
3) If f_{max} is next to $f_{flicker}$ in the spectrum, set $amp(f_{flicker}) = amp(f_{max})$.
4) If $amp(f_{flicker})/amp(f_{max}) > threshold$ then conclude that a peak is present. During experiments the optimum $threshold$ was found to be 0.8.

where $amp(F)$ is the amplitude of the frequency F obtained by FFT.

The relative alpha power value and presence of SSVEP were continuously sent to the game PC via TCP.

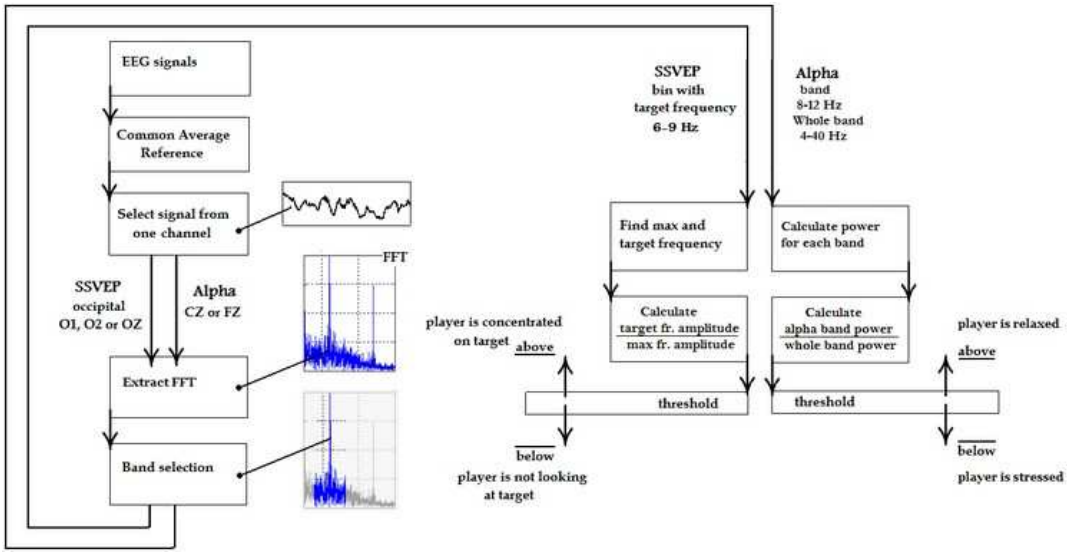


Fig. 7: The signal processing pipeline of Bacteria Hunt.

5 EXPERIMENTS

The overall goal of the project was to develop a game that would be suitable for the use as experimental platform to answer research questions related to BCI. From the underlying research questions on applicability and combinability of BCI control in a game specific hypotheses were posed:

Hypothesis I: The use of a positive neurofeedback paradigm, based on the reward of high alpha values, as a control modality results in an increase in alpha power and in a state of higher relaxation and less tension.

Hypothesis II: The combination of positive alpha neurofeedback and SSVEPs causes no detrimental effects. As alpha feedback should result in a state of relaxed attentiveness, we assumed that the attention on the flickering SSVEP stimuli should not necessitate a change of overall relaxation state.

5.1 Methodology

In order to test the hypotheses stated above, an experimental protocol was devised. Participants were asked to play two versions of a game. Each version was constructed from three levels, namely *K*, *KA*, and *KAS* (see §4.1.3). In keyboard only level *K* the participant had time to get acquainted with the game. Furthermore, it can be used as an alpha baseline condition later on. The difference between both games was in the way the alpha neurofeedback was applied. In the positive feedback version (*pF*) an increase of alpha yielded an increase in controllability of the game. In the negative feedback version (*nF*) we inverted the relationship between alpha level and controllability.

Five participants (2 female, mean age: 26) took part in the experiment. The participants were seated in front of the notebook running the game (1.8 GHz Pentium M). They read and signed an informed consent and filled in a questionnaire assessing prior drug consumption and amount of sleep. After that the electrode cap was placed and the electrodes connected. 32 Ag/AgCl Active electrodes were placed according to the 10-20 system [13]. The EEG signals were recorded with 512 Hz sample rate via a BioSemi ActiveTwo EEG system and processed and saved on a separated data recording and processing notebook (2.53 GHz Quadcore) running BioSemi ActiView software.

The blocks contained the 3 games in the following order: *K*, *KA*, and *KAS*. Each game lasted for 4 minutes. That made a total duration of 12 minutes per feedback session, excluding small breaks between the games. After each feedback session the participants were given a questionnaire to evaluate their experience

during the game session.

5.2 Analysis

To test the first hypothesis the alpha power was analyzed as an objective indicator and the user experience as a subjective indicator. Specifically a higher level of alpha power for the positive feedback condition compared to the negative feedback condition was predicted, as alpha power increases were rewarded in the former and punished in the latter.

The Game Experience Questionnaire GEQ [11] was used to measure user experience according to the concepts of competence, immersion, flow, tension, challenge, negative, and positive affect in separate scales. We added a control scale that assessed the felt controllability of the player in each feedback condition. It was predicted that positive neurofeedback would lead to a decrease of tension and subsequently an increase of positive affect.

To test the second hypothesis we analyzed only the objective indicator of relaxation, i.e. alpha power. We compared the power in the alpha band between the *KA* and the *KAS* condition of the positive feedback session. We expected an equal level of alpha power, thus no interference from the SSVEP stimulation in *KAS*. Additionally, to check for temporally limited interactions between the two BCI paradigms, we compared the level of alpha power before and during SSVEP stimulation and expected also there an equal amount of alpha.

5.3 Results

The analyses on the data collected have two sorts of implications. They provide conclusions about applicability and combinability of BCIs while answering the hypotheses posed previously.

5.3.1 Applicability of BCI

As result of the first hypothesis, concerning the applicability of a BCI paradigm in a game, an effect of the applied neurofeedback on alpha power and user experience was predicted. However, neither objective nor subjective indicators for an effect of the feedback were found (see table 5). No significant difference in mean alpha band power could be shown between the games applying positive and negative feedback. Accordingly, there was no significant difference in the user experience between the positive and negative alpha-feedback conditions.

The failure to find an effect of the feedback on alpha power and user experience might have different causes. In general, it might be due to the small sample size of 5 participants. Furthermore, for both feedback conditions the participants were instructed to relax, which might have lead them to relax in both conditions despite the difference in feedback. Possible differences might be covert then by a floor effect. Complying with this possible caveat, table 5 shows very low scores for the tension scale. This lack of excitement was also reported by the participants in informal interviews after the experiment. To exclude this possibility the stress level during gaming would have to be increased, possible by a higher difficulty and a more dynamic and faster nature of the game.

Interestingly, we found a marked difference of the pre-SSVEP alpha power between *nF* and *pF* conditions, with higher alpha power for the *pF* condition ($p \leq 0.006$). In the absence of an overall difference of alpha power this effect seems contradictory. However, it could indicate the effectiveness of alpha feedback for conditions with higher difficulty, as the *KAS* conditions were potentially more stressful due to the more difficult SSVEP-based scoring. This effect might be too small though to be reflected in overall alpha power and the conscious experience of the players assessed via the GEQ.

5.3.2 Combinability of BCI

As a result of the second hypothesis, concerning the combinability of two BCI paradigms in an application, we expected no interaction of both paradigms, that is no effect of SSVEP on alpha power. Accordingly, we found no significant difference in mean relative alpha power between *KA* and *KAS*.

Unexpectedly, an influence of the SSVEP stimulation on alpha power was found for the alpha feedback condition *pF*. Specifically, alpha power before SSVEP stimulation was signifi-

	negative F mean	std	positive F mean	std	ttest(*nF*,*pF*) H	P
Questionnaire data						
competence	2,03	0,81	2,13	0,81	0	0,850
immersion	1,67	1,10	1,33	0,75	0	0,230
flow	2,17	0,72	1,93	0,85	0	0,535
tension	0,97	0,69	0,87	0,62	0	0,591
challenge	1,47	0,55	1,40	0,25	0	0,688
negative	1,20	0,74	1,37	0,59	0	0,561
positive	1,90	0,74	1,73	0,51	0	0,430
control	2,35	1,05	2,15	0,68	0	0,767
EEG data						
α *KA*	0,18	0,02	0,18	0,01	0	0,723
α *KAS*	0,18	0,02	0,18	0,02	0	0,593
preSSVEP α	0,18	0,01	0,19	0,01	1	0,006
SSVEP α	0,18	0,02	0,18	0,01	0	0,938
preSSVEP α - SSVEP α	0,00	0,01	0,01	0,00	1	0,006
Behavioral data						
Score *K*	4348,34	1118,47	4343,24	1295,33	0	0,991
Score *KA*	4040,04	1038,16	2909,89	1491,15	0	0,176
Score *KAS*	496,70	798,15	205,53	740,25	0	0,621

TABLE 5: The questionnaire results for positive (*pF*) and negative (*nF*) feedback sessions. The items were assessed on a scale from 0 to 4, with 0 indicating the least, and 4 the most agreement to the concepts assessed. The EEG was analyzed in terms of mean relative alpha band power on the Fz electrode during the game 2(α *KA*) and game 3 α *KAS*), the mean alpha power in the 4 seconds before SSVEP stimulation (preSSVEP α) and during SSVEP stimulation (SSVEP α). The minimum observed and the maximum were 0.15 and 0.23, respectively. The behavior was analyzed as points scored in the game.

cantly higher than alpha power during SSVEP stimulation ($p \leq 0.0001$).

The contrast of the pre-SSVEP alpha between the different feedback sessions discussed before, showed that this effect resulted from the higher alpha power during the pre-SSVEP epochs of the *pF* condition. This suggests that positive feedback might work in more difficult conditions, leading to higher alpha. Consequently, the SSVEP stimulation interferes with this state of higher alpha and potentially greater relaxation. This interference could be due to several mechanisms. For example, it could be caused by purely dynamic characteristics of the stimuli. As we compute the relative alpha power, an increase of power in SSVEP-related frequency bands would automatically lead to a decrease of the alpha power. On the other hand, it could be a result of the task that is executed during the stimulus presence.

5.4 Discussion

It was hypothesized that the positive feedback would lead to higher levels of alpha power, lower tension, and more positive affect. No general alpha increase for positive feedback could be shown. Similarly, no effect of the alpha feedback was found in terms of user experience.

Furthermore, we hypothesized that SSVEP stimulation would have no side effect on the alpha power. This was true for the comparison of alpha level between the levels *KA* and *KAS*. However, a difference between the alpha power before SSVEP stimulation to the alpha power during stimulation was observed for the positive feedback condition. This difference was due to a higher alpha power before stimulation. In the negative feedback condition no such difference was found. Hence, we argue that at least for the *KAS* condition the positive alpha feedback led to higher alpha, which was then attenuated by the SSVEP stimulation.

To explore the applicability and value of neurofeedback in computer games the manipulation of the difficulty level of the application might be interesting. Further studies of the influence of SSVEP on alpha power could focus on the origin of the decrease of alpha power.

6 Discussion

We have developed a computer game that uses two BCI paradigms in addition to a conventional control via a keyboard. In pilot studies different BCI paradigms were explored to determine the viability within the game environment and to develop algorithms.

Despite the efforts to develop a BCI pipeline that could be used without prior training of the subject or the classifier, the results of our analyses and interviews with participants suggest that a subject-dependent classifier would overcome the shortcomings of the general classifiers applied. For example, the power in the SSVEP frequency band varied among subjects. Thus a subject-dependent classifier, applying a threshold based on a prior training session, could increase the control of the subjects over the avatar. Similarly every individual has his/her own range for the alpha power measured. In pilot experiments, a generic range determined by observing the lowest and highest alpha power values of the majority of the subjects was used. A more elegant approach could be adapting this range per subject. This can be accomplished via a training session run before the game or by dynamically adjusting the values during the game play.

The SSVEP detection method was developed so as to use signals from only one EEG channel (O2) but as shown in §3.1 SSVEP can be detected in all three occipital channels. Thus, information from these channels can be combined to make detection more robust. Also, instead of relying on peak detection solely in the stimulation frequency, the peaks at the second or later harmonics can be employed. In addition, the parameters like the bin size and the reference amplitude can also be tailored for optimized performance.

The original intention of the project was to build a multiplayer game. For this purpose, during the workshop, multiplayer versions of the game and the analysis pipeline were implemented. However, during the workshop, it was discovered that the proprietary software delivered with the EEG hardware could not send information from multiple systems as necessary for online multiplayer BCI. When this restriction is revoked, the multiplayer version can also be tested.

The results reported in this paper are based on 5 participants and especially the non-findings concerning the first hypothesis might be due to the low number of samples. Despite the missing overall effect of neurofeedback, a difference between alpha power in the positive and negative feedback condition was found in the pre-SSVEP epochs of the *KAS* games. This effect might indicate that the failure to find significant differences in alpha power and user experience might be due to a floor effect caused by the high degree of relaxation in both feedback conditions. To avoid this effect in future studies, it is suggested to increase the difficulty level and thereby decrease the overall state of relaxation during the game.

Furthermore, negative feedback was employed to examine the effect that feedback has on the player. While this method is in principle valid to determine the existence of an effect, it does not enable the differentiation of the effects of positive and negative feedback. To delineate these, an additional no-feedback condition could be employed.

A possible problem of the interpretation of the results could also result from the game instructions given before the experiment. The participants were informed that relaxation would increase controllability. This might have caused confusion or other negative effects when the opposite effect was realized in the negative feedback condition. Differences between feedback conditions could thus be due to this clashing expectations rather than due to the effect of feedback directly.

Finally, the application of small user experience questionnaires after each game would enable the delineation of the effect of the different BCI controls on user experience. However, the difficulty lies with the avoidance of confounds due to entirely different game mechanics, which could also be implemented by other techniques.

7 Conclusion

With the new branch of the BCI research which now considers non-disabled people also as the

potential users, BCIs started to be incorporated into everyday applications, like computer games. BCI is an invaluable communication channel that can directly convey information no other modality can: the state and intention of the user. This information can be used to control, modify or adapt a game tailored to the player, and could thereby provide added value. However, the extent that BCIs can tolerate the dynamic environment of games or the existence of other modalities is still under investigation.

In this paper we proposed a design space for physiological game design and described a multimodal, multiparadigm BCI game called Bacteria Hunt which is controlled by keyboard, SSVEP, and relative alpha power. We investigated how well different paradigms can be used together and what effect positive vs. negative neurofeedback creates. The experiments conducted on the initial prototype game developed revealed that in the tested setup no significant difference in mean alpha band power and in user experience between the games applying positive and negative feedback were found. Furthermore alpha power before SSVEP stimulation was significantly higher than alpha power during SSVEP stimulation. Therefore one needs to consider this when combining these two paradigms for control.

Bacteria Hunt is suitable for use as an experimental platform for BCI research. We have the intention to continue experimenting on this platform, especially within multimodality and interaction domains.

Acknowledgments

The authors would like to thank Boris Reuderink for his help with the BCI pipeline.

This research has been supported by the GATE project, funded by the Netherlands Organization for Scientific Research (NWO) and the Netherlands ICT Research and Innovation Authority (ICT Regie), by the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science, and by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 231287 (SSPNet).

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Christian Mühl earned his Master's degree in the Cognitive Sciences in 2007 at the University of Osnabrück, Germany. His education was focused on neuroscientific methods, specifically electroencephalography. Since then he is working as a research assistant in the Human Media Interaction Group at the University of Twente, The Netherlands. In his PhD thesis he searches for neurophysiological and physiological correlates of affective states in the context of brain-computer interaction.

Hayrettin Gürkök received his B.S. and M.S. degrees in Computer Engineering from Bilkent University, Turkey. His M.S. thesis was on linguistics and text retrieval. He is currently a member of the Human Media Interaction group at the University of Twente. He is conducting research on multimodality and realistic settings for BCIs. His research interests also include human-computer interaction, social computing and information retrieval.

Danny Plass-Oude Bos got her first experience with online BCI during an internship at the University of Nijmegen in 2007. There she implemented physiological artifact detection in an online EEG-based BCI system. In 2008 she obtained her master degree in Human Computer Interaction, looking into the user experience of using BCI for games. At the moment she is working as a PhD student at the University of Twente, still attempting to merge BCI with HCI by researching how BCI can be made a more intuitive means of interaction.

Marieke E. Thurlings started as a PhD candidate at TNO (The Netherlands Organization for Applied Scientific Research) and at the Utrecht University, in 2008. She currently investigates navigating in Virtual Environments using brain signals as an input, involving the fields of Brain-Computer Interfacing, Games and Virtual Worlds. Marieke is especially interested in using event-related potentials, such as P300s and SSEPs, and exploring covert attention to probe stimuli to evoke these, e.g. by presenting them in unconventional modalities. Marieke obtained her Master of Science degree in Design for Interaction from the Delft University of Technology.

Lasse Scherffig is a PhD student at the Lab3, Laboratory for Experimental Computer Science of the Academy of Media Arts Cologne (Germany). Since July 2006 he also is a member of the artistic/scientific staff of the academy. He graduated in cognitive science at the university of Osnabrck (Germany) and received a M.Sc. in digital media from the University of Bremen (Germany). His dissertation project focuses on the relation of action and perception in Human-Computer Interaction.

Matthieu Duvinage graduated as an electrical engineer in signal processing and telecommunications from the Facult Polytechnique de Mons (Belgium) and SUPELEC (France) in june 2009. He also got a master of fundamental and applied physics from the University of Orsay (France) in june 2009. He has just started a PhD at the Signal Processing and Circuit Theory Lab at the University of Mons (Belgium) on the development of a neuroprothesis to control an artificial leg via BCI.

Alexandra A. Elbakyan graduated from KazNTU with a Bachelor degree in IT in June 2009. She conducted a study regarding person identification by EEG in her final year thesis. She is going to continue her research in brain-computer interfaces and brain implants.

SungWook Kang received the B.S. degree in electronic communication engineering from the Kwangwoon University, Seoul, Korea, in 2009. He is currently working towards the M.S. and Ph.D degree at Biocomputing Lab., Dept. Information and Communication, Gwangju Institute Of Science and Technology. His research interests include bio-signal processing especially EEG and MEG, feature extraction, information theory and brain-computer interface.

Mannes Poel is assistant professor in the Human Media Interaction group at the University of Twente. His main research involves applied machine learning for vision based detection and interpretation of human behavior and the analysis and classification EEG based brain signals.

Dirk Heylen is associate professor in the Human Media Interaction group at the University of Twente where his research involves the automatic interpretation of verbal and nonverbal communication and the of modeling conversational and cognitive functions of embodied conversational agents. His work on the analysis and synthesis of nonverbal communication in (multiparty) conversations has been concerned with gaze, and head movements in particular. His research interests extend to the study of physiological signals that can be used to interpret the mental state of user.

Video Navigation Tool: Application to browsing a database of dancers' performances

D. Tardieu*, R. Chessini*, J. Dubois*, S. Dupont*, S. Hidot*, B. Mazzarino†, A. Moinet*,
X. Siebert*, G. Varni† and A. Visentin†
* TCTS Lab - Faculté Polytechnique de Mons, Belgium
† InfoMus Lab, DIST - University of Genova, Italy

***Abstract*—The purpose of this project is to provide a method and a software for browsing a dance video database. This work has been done in collaboration with the artistic project "DANCERS!" [1]. A set of features describing dance are proposed, to quantify the gesture of the dancer, the usage of its personal space, the occupation of the stage and the temporal structure of the choreography. These quantities are extracted using the EyesWeb XMI platform [2], to which new features were added. The description of the video is used to compute the similarity between the dancers and then to help the exploration of the database. The management of the video and feature collection is done using the Mediacycle software [3] which has been extended from sounds and images to videos databases.**

I. Introduction

This project aims at creating a navigation software for browsing video databases. In the context of the eNTERFACE09 workshop, we focused on dance videos, in association with the artistic project "DANCERS!" [1]. To allow content based navigation in the database, features describing the performance have to be extracted from the video. We propose a set of features that can be divided into three categories: first, gesture features that describes how a dancer moves in the closely surrounding space (the kinesphere); second, space occupation features describing how a dancer uses the whole stage space; third, features describing the temporal structure of the choreography.

The feature extraction is done in three steps. First, the silhouette of the dancer is extracted using a simple background subtraction technique and the bounding box is computed. Then frame by frame features (also called temporal features) are calculated. Finally, those temporal features are summarized using several statistical methods. One of the main contributions of this project is the proposition of a reduced set of features aiming at summarizing the characteristics of the performance. More precisely, we propose a low-dimensional set of features for the description of the space occupation and a technique for the discovery of the temporal structure of the choreography borrowed from the music analysis field. The extraction of the temporal features was performed using the EyesWeb XMI software platform [2] and in particular using the EyesWeb Gesture Processing Library [4]. A new EyesWeb module for rotation detection was also developed. The global features are computed by the Mediacycle software which is as well in charge of the feature database organization and browsing. Manual annotation of the videos were also performed, to allow the objective validation of the extracted feature.

The paper is organized as follows : In the first section we describe the dance video corpus that has been used and the manual annotation. In the second section we detail the proposed features and their extraction method and finally we give an overview of the navigation system.

II. Dance Video Corpus

This project focuses on short videos of dancer performances, that have been filmed in a calibrated setup described below. It is associated with the artistic project "DANCERS!" [1] of the choreographer Bud Blumenthal, which aims at providing a high quality audiovisual database of professional dancer performances, that can be browsed via a website. The website will be presented in a public installation in November 2009 at the Biennale of Charleroi-Danses [1] in Belgium.

A. Setup

The stage setup is described on Fig. 2: each dancer performs a two-minutes improvisation in the space colored in red, either in silence or with a piece of music. Two videos are recorded: one from the front (labeled "EX1" on the picture) and one from the top. For technical reasons, the top camera (wide angle) was placed about 6 meters from the floor, and the sides of the stage are slightly cut on the top-camera video recording (see Fig 1, right). The front videos are recorded in High Definition (HD), 25 frames per second, interlaced, using the *XDCAM-EX* codec.

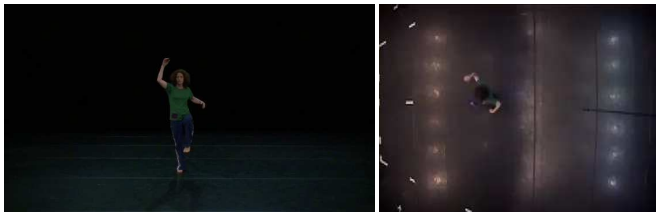

Fig. 1. Snapshot of a front and top videos (dancer: Claire O'Neil).

About 140 videos (two trials per dancer) were available at the time of the eNTERFACE09 workshop, and more recordings are planned after the summer. Finally, it is important to

[1] www.charleroi-danses.be

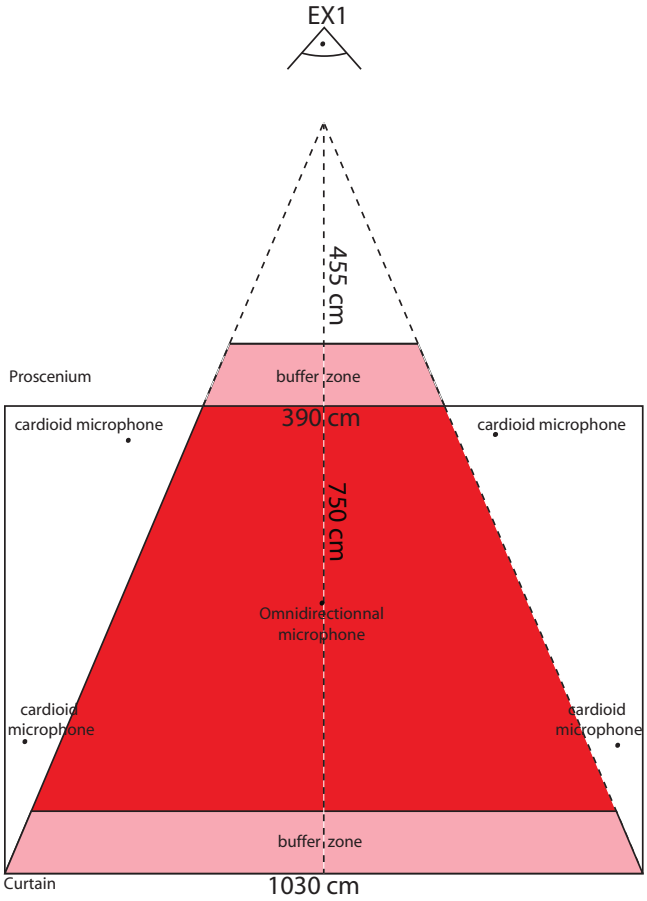

Fig. 2. Top view of the recording stage setup. The front camera is labeled "EX1". The dancer can occupy the red area, delimited by buffer zones in pink. Microphones are placed around and above the stage to record.

note that no sensors were embedded on the dancers, so that the analysis fully relies on raw video analysis.

B. Video annotation

To be able to perform an objective evaluation of the proposed features, the video were manually annotated during the workshop. The annotation criteria are the following:

- smoothness: the position evolves in a natural and fluid way;
- rigidity: the body keeps a rigid posture while moving in space;
- number of attacks: an attack is defined as a moment when the dancer changes abruptly the speed of his/her movements;
- twirl: the dancer performs a rotation while standing or jumping;
- laying rotation: the dancer rotates while being on the ground or with a very low center of gravity;
- number of jumps: small and big jumps are grouped into this category;
- video cut: in some videos the dancer becomes invisible, either by exiting on the side, or by reaching the dark region at the very back of the stage. Note that the exit on the side can be deliberate, or can be only apparent on the top shot, which does not cover the whole stage, as mentioned above;
- segmentation of the choreography: this attempts to grasp changes in the "intention" of the dancer;
- amount of gestures: in this context a gesture is considered as a small motion that seems to engage in a communication;
- temporal rhythm: as opposed to the concept of "attack" defined above, this concerns the longer-term rhythm of the performance (e.g., slow at the beginning, growing at the middle, then slowing down again).

The first seven characteristics can be considered as objective, while the latter three are more subjective. Additionally, comments can also be provided by the person doing the annotation, to refine the description of some features or to try to verbalize the scenario communicated by the dancer.

III. Dance motion description

A. Automatic top and front videos alignment

To correlate the features extracted from the front and top cameras, the two corresponding videos have to be synchronized, which was not done during the live recordings. Several techniques could be used to align the videos in time, for example using the sound stream to match the "clap" signal. We have chosen to focus on the image and to detect the moment when the dancers enters the stage. For the top shots, this amounts to finding when the first pixels are moving (after noise filtering). However, the first pixels to move on the front shot are coming from the clapping signal of the cameraman. We thus had to detect when the dancer enters the stage after the clap of the cameraman, which was done by a background subtraction followed by a blob detection, as described below.

B. Background subtraction and silhouette detection

The analysis of the videos implies detection and tracking of the dancer's silhouette. This essentially involves background subtraction, and is complicated by two factors. On the one hand, the stage is somewhat shiny and reflects the dancers' image, especially when they are wearing light/bright clothes. On the other hand, some dancers have a dark skin color, dark hair, or are wearing dark clothes. Therefore, a simple background subtraction with a binary threshold will either cut some parts of the dancer (threshold too high), or include its reflection on the dance floor (threshold too low). We thus tried to find a compromise between these two extremes, but it is difficult to define automatically the best threshold, without checking visually. Indeed, since the objective of our work it to provide an automatic and autonomous way to extract motion characteristics from the videos, the background subtraction has to be fast and efficient for all the movies currently available, as well as for new ones. Other approaches were tried (e.g

statistical and adaptive methods), but those either failed to provide a uniform solution for all the movies of the corpus or required much computational power, for a marginal gain in accuracy. We finally used an analysis of each color channel separately. Indeed, the dance floor contains about twice less red (R) than green (G) or blue (B). Therefore, the background detection was generally performed on the R channel, which reduces the risk of including the reflection of the dancer. The B and G channels can then be added with a higher threshold to eventually fill in the dominantly blue or green clothes of some dancers. The background itself was computed by finding the pixel-per-pixel median of the image over time.

C. Temporal features

In the following sections, we make a distinction between the *General Space* and the *Personal Space* or *Kinesphere*, concepts first introduced by Laban [5]:
"Whenever the body moves or stands, it is surrounded by space. Around the body is the sphere of movement, or Kinesphere, the circumference of which can be reached by normally extended limbs without changing ones stance, that is, the place of support. The imaginary inner wall of this sphere can be touched by hands and feet, and all points of it can be reached. (...) Thus, in actual fact, he never goes outside his personal sphere of movement, but carries it around with him like a shell. "

1) General Space features: General Space features describe how dancers use the stage during the performance. For this analysis the dancer's movement can be approximated by the movement of a point in space (on stage in this case). In our work we considered this point to be the center of gravity (CoG) of the dancer, and we extracted the following low-level characteristics from each frame recorded by the top camera:

- position (x,y) of the CoG, normalized with respect to the dimension of the image;
- the velocity of the CoG along the x and y axes, calculated using a small window of 3 points in each direction;
- the acceleration of the CoG along the x and y axes, calculated the same way.

2) Personal Space features: Personal Space features describe the movement inside the kinesphere. They can be related to the nature of the movements and, to some extent, to the quality of the performance. These features have been implemented following the theory of Effort [6], theories from cognitive science and psychology such as Boone and Cunningham [7]. In our work we focused on the following measurements (see [8] for further details):

- the *Quantity of Motion* (QoM) corresponds to the fraction of the dancer's body that moves in time, and is related to the energy;
- the *Contraction Index* (CI) provides information on the spatial occupation of the kinesphere by the body. More specifically, it measures the contraction/expansion of the dancer's body with respect to its centre of gravity and can be calculated as the ratio between the area of the silhouette and the area of the rectangular box surrounding it (the so-called "bounding box"). For example, if a dancer extends his/her limbs far from the body, the CI will be low (close to 0). On the contrary, if a dancer keeps his/her limbs close to the body, the CI will be high (close to 1).
- the Bounding Box dimensions (width and height).

3) Rotation detection: We adapted an existing algorithm [9] to detect when a dancer rotates with respect to the top camera. The algorithm first extracts the optical flow of the dancer by the Lukas-Kanade method [10]. This gives essentially a vector field corresponding to the pixels that have moved from a frame to another. A threshold is then applied to the magnitude of these vectors to detect fast-moving points ("high-energy points", marked as white dots in the left panel of Fig. 3). The curl of the resulting vector field then indicates rotations of high-energy points in the plane parallel to the top camera. Indeed, when the maxima of the curl are correlated in several successive frames, we consider it to be a meaningful rotation of the dancer. The maxima of the curl of the optical flow for a few successive frames are shown on Fig. 3 (yellow points in the middle panel). On Fig. 3 (right panel) the variance of the relative distance between these high-energy points is computed over time. A low variance thus indicates regularly spaced points corresponding to a concerted rotation. In this example it corresponds to a rotation of the legs of the dancer, around the green point in the middle panel of Fig. 3. At the resolution of the images, it is possible to distinguish a rotation, but not to differentiate between the rotation of a part of the body and a full body rotation. We implemented this algorithm in the EyesWeb platform using its Software Development Kit.

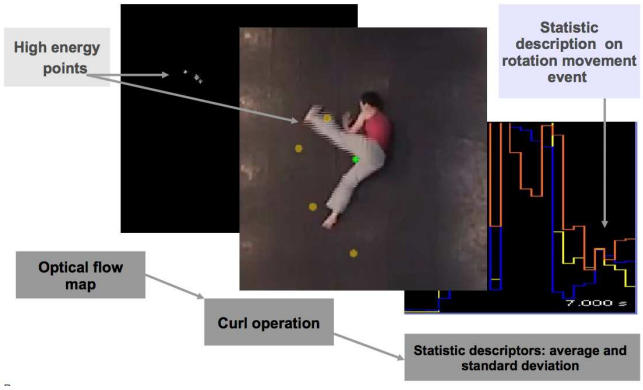

Fig. 3. Rotation detection based on the high energy points from the curl of the optical flow. The white dots on the left image are the points that moved most (the extremity of the dancer's left leg). The yellow dots on the central image are the maxima of the curl over time and are regularly spaced. The right image shows the standard deviation of the rotation movements over time. A small deviation indicates a concerted rotation.

D. Global features and Temporal Model

After extraction of the features for each frame of the video, statistical tools are necessary to summarize this huge amount

of information. Indeed, two-minutes videos recorded at 25 frames per second represent about 3000 frames. For each frame, all the above features are extracted, leading to several thousands of data. It is therefore necessary to summarize them to obtain a small set of relevant features that could be further linked to a semantic description of the performance.

1) Mean and standard deviation: The simplest way to summarize the temporal features is to calculate their basic statistics such as mean and standard deviation. Whereas it can be meaningful for some features, other methods need to be explored. For instance the mean position of the dancer on the stage could be similar (e.g., the center of the stage) for very different kind of trajectories. Other important characteristics of a choreography are its temporal evolution and its segmentation, which we propose to summarize in two ways. The first one focuses on the dancer's space occupation. It is based on a three dimensional mid-level description of the trajectory and on the most occupied place on the stage. The second one focuses on the segmentation of the choreography.

2) Space occupation: The stage occupation can be studied using the Occupation Rate concept [11]. The image was divided in a 10 by 10 grid (corresponding to 100 cells of approximately 80x70 cm each) to compute a space-occupation map representing the percentage of time that the dancer spends in each cell. From this map we can extract different global characteristics of the performance:

- the size of the occupied space (large vs. small global trajectory),
- the compactness vs. sparsity of the trajectory,
- an indication about the preferred zone where dancers developed their improvisation with respect to the position of the camera (in terms of proscenium, centre or rear of the stage).

These notions are illustrated on Fig. 4, showing our results for four different types of dancers.

Other features of the dancer's performance can be extracted from the relationships between some of the above-mentioned descriptors, for example:

- the distance between the CoG of the trajectory and the most occupied cell.
- the distance between the most occupied cell and the camera

The first distance gives an indication about the time distribution in space, while the latter provides information about the emphasis that the dancer gives to a special sector of the stage.

3) Choreography segmentation: To characterize the temporal development of the choreography we use the segmentation method of [12] that was initially applied to music. This method is based on the computation of a feature similarity matrix. The similarity matrix can be computed for any feature or any set of features. It is obtained by computing the similarity between all the time frames of the feature set. The similarity matrix M is defined as :

$$M_{i,j} = S(d_i, d_j) \quad (1)$$

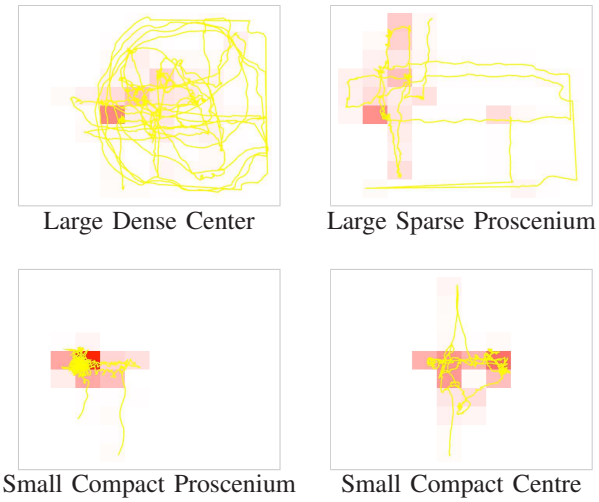

Fig. 4. Results of the General Space Occupation for four different dancers. The yellow line is the trajectory of the Center of Gravity of the dancer, seen from the top. The space is divided into cells, colored in red (the darker the red, the most occupied the cell). The front camera is located on the left (not shown).

where S is the similarity measure and d_i is the value of the feature, that can be multidimensional, at frame i. An example of such a matrix is given on the middle plot of Fig. 5. It is computed on the speed of the dancer (top plot). High similarity is represented by white color and low similarity by black color, the axis are the frame numbers. Looking at this figure we can see that the choreography can be divided into three main segments in term of speed. This is showed by the three big white squares along the diagonal. We can also notice that the first segment (between frame 0 and 80) and the last one (frame 640 to the end) are similar by looking at the to left white rectangle.

From this matrix we can extract the so-called novelty score. This score is computed by correlating the matrix with the appropriate kernel (see [12] for details). Extrema in this score correspond to large changes in the choreography. In the bottom plot of Fig. 5 we can see that the two biggest peaks corresponds to the limits of the previously mentioned segments. Then by using this measure we can automatically segment the choreography and also find repeating segments. This method allows to find a temporal structure of the choreography and to describe the temporal evolution of the feature. There are at least two open question on the use of this temporal structure for dance similarity measure. The first one is the choice of the feature to be used in the calculation of the similarity matrix. Since any feature or set of feature can be used, we can obtain many different time structure. The second question is: "how to compare two choreographies using this representation ?". We can choose to either extract a description from the segmentation itself, such as the number of segments or the mean segment length, or to find direct comparison measure of the segmentation. Those question have not been addressed yet.

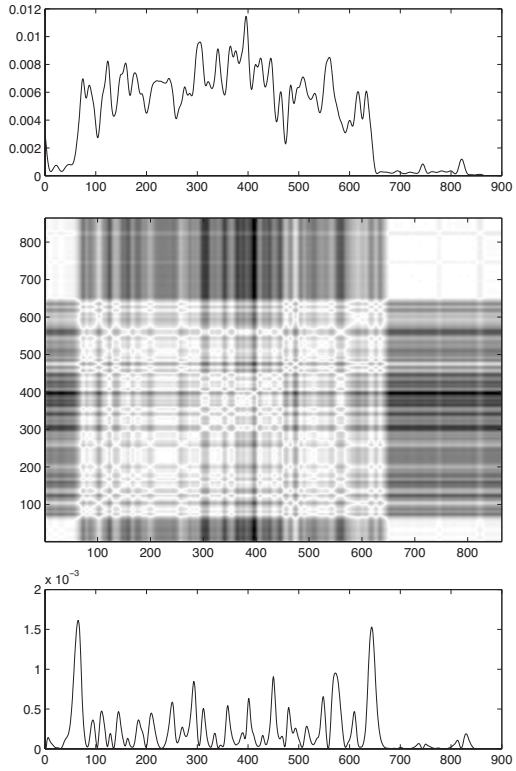

Fig. 5. Speed of the dancer (Top), Similarity matrix computed on the speed (middle) and novelty score (bottom)

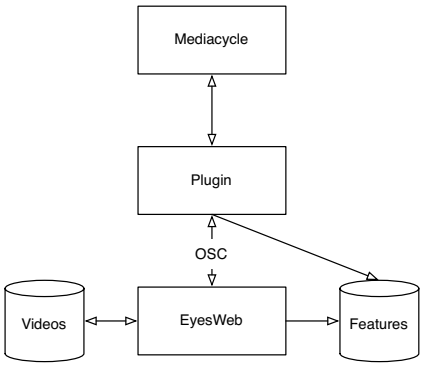

Fig. 6. Architecture of the system

IV. System Implementation

A. Overview

The system for analysis and navigation is mainly composed of two parts, EyesWeb and Mediacycle, that are both described in the following sections. EyesWeb is in charge of the extraction of the temporal features whereas Mediacycle compute the global features through a plugin and manage the database. Communication between the Mediacycle plugin and EyesWeb is done with the OSC protocol. The global architecture is shown in Fig. 6.

B. EyesWeb

EyesWeb XMI (for eXtended Multimodal Interaction) is a platform for real-time multimodal processing of multiple data streams in the direction of multimodal and cross-modal processing. EyesWeb XMI allows to: (i) connect a large number of heterogeneous external devices; (ii) exploit features of multi-processors/multi-core architectures; (iii) use optimized type system and software modules; and (iv) synchronized multimodal data streams having different clocks. The platform, distributed for free on the web www.eyesweb.org, consists of two main components: (i) a kernel, and (ii) a graphical user interface (GUI).

The kernel is a dynamically pluggable component which takes care of most of the tasks performed by EyesWeb XMI. in particular the kernel contains the EyesWeb Execution Engine which manages the patch execution, handles data flow, synchronization and notification of events to GUI.

The GUI manages interaction with the user and provides all the features needed to design patch. It is noteworthy that the kernel and the GUI are not tightly coupled: it means that several GUIs may be developed for different applications.

EyesWeb XMI consists of a number of integrated hardware and software modules, implemented in C++, which can be easily extended and interconnected. It includes a development environment and a set of libraries of reusable software components that can be assembled by the user in a visual language to build applications called *patches*. EyesWeb libraries include:

- Input-Output: support for frame grabbers (from webcams to professional video-cameras), wireless on-body sensors (e.g. accelerometers), audio, MIDI input, serial, TCP/IP, UDP, OSC, visual and auditory displays;
- Libraries for data manipulation as Image and Video, Audio, Math and filters, Midi, Machine Learning;
- Expressive Gesture Processing: a collection of software modules devoted to an automated analysis of human movement and extraction of expressive gesture cues; and
- Expressive Gesture and Social Processing: a collection of software modules devoted to an automated extraction of social cues like, for instance, synchronization index and leadership index.

C. Mediacycle

Mediacycle is a Software developed by the TCTS laboratory in the university of Mons in the context of the Numediart project. The goal of this software is to allow easy management of multimedia collections and content based browsing through the database. It is composed of three entities : the kernel, the GUI and plugins. The kernel manages the features and media database, it allows to perform similarity queries via a nearest neighbor search and k-means clustering. The kernel uses the plugins to compute the media features. Until now three plugins have been developed for sound, images and dance video analysis. The interface showed in Fig. 7, developed

in Cocoa and OSG, allows to display the media according to similarity information. The architecture is meant to allow easy extensions, such as the addition of new plugins for media analysis or the implementation of new user interfaces.

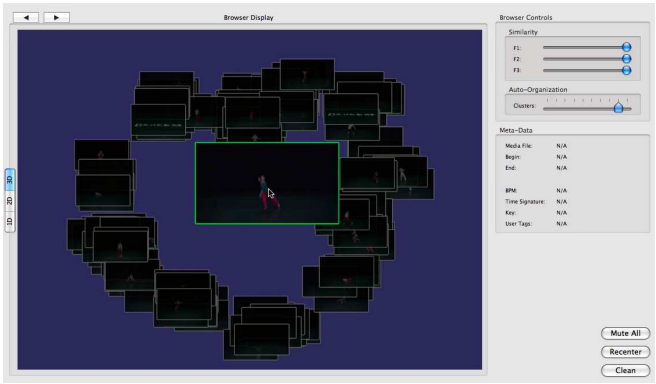

Fig. 7. Overview of the MediaCycle software, to navigate the video database based on the similarity between the videos. The sliders on the top right can be used to defined the weights of the different features extracted from the videos.

D. OSC Communication

The Open Sound Control [13] is used to exchange information between EyesWeb and MediaCycle in two ways :

1) MediaCycle → EyesWeb : MediaCycle browses the directories containing the videos, sends their names by OSC to EyesWeb
2) EyesWeb → MediaCycle : after processing the videos, EyesWeb returns the extracted features to MediaCycle.

V. Conclusion

In this project we have addressed several aspects of the realization of a dance video browsing software. We proposed a set of features allowing the description of the dance performances. The proposed set allows the description of three different aspects of the performance. First a compact description of the stage occupation based on the position of the center of gravity of the dancers, second a description of the gestures of the dancers and of the usage of its personal space mainly based on the contraction index and the quantity of motion and finally a method based on feature similarity matrix to extract the temporal structure of the choreography. Those features will allow content based navigation in the database of the DANCERS! project. The proposed description is low-level and many research is still necessary. First of all the description of the personal space can be extended. For instance description of the smoothness or the impulsiveness of the gesture can be added [14]. Second the use of the temporal structure of the features still needs to be studied. Some open questions regarding the comparison of temporal structures, the choice of the features have been raised in the project but need further research. Finally an objective evaluation of the proposed features has to be performed in the context of database exploration and query by similarity. A first step in this direction has been done by selecting manual annotation criteria and performing a first annotation.

VI. Acknowledgements

We would like to thank Bud Blumenthal, the members of his collective (`www.bud-hybrid.org`) and the dancers for making it possible to work with their high-quality videos.

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AVLaughterCycle: An audiovisual laughing machine

Jérôme Urbain[1], Elisabetta Bevacqua[2], Thierry Dutoit[1], Alexis Moinet[1], Radoslaw Niewiadomski[2], Catherine Pelachaud[2], Benjamin Picart[1], Joëlle Tilmanne[1], and Johannes Wagner[3]

[1]TCTS Lab, Faculté Polytechnique, Université de Mons, Boulevard Dolez 31, 7000 Mons, Belgium
[2]CNRS - LTCI UMR 5141, Institut TELECOM - TELECOM ParisTech, 46 rue Barrault, 75013 Paris, France
[3]Institut für Informatik, Universität Augsburg, Universitätsstr. 6a, 86159 Augsburg, Germany

***Abstract*—The AVLaughterCycle project aims at developing an audiovisual laughing machine, capable of recording the laughter of a user and to respond to it with a machine-generated laughter linked with the input laughter. During the project, an audiovisual laughter database was recorded, including facial points tracking, thanks to the Smart Sensor Integration software developed by the University of Augsburg. This tool is also used to extract audio features, which are sent to a module called MediaCycle, evaluating similarities between a query input and the files in a given database. MediaCycle outputs a link to the most similar laughter, sent to Greta, an Embodied Conversational Agent, who displays the facial animation corresponding to the laughter simultaneously with the audio laughter playing.**

***Index Terms*—laughter, virtual agent, speech processing.**

I. Introduction

LAUGHTER is an essential signal in human communications. It conveys information about our feelings and helps to cheer up our mood. Moreover, it is communicative, eases social contacts and has the potential to elicit emotions to its listeners. Laughter is also known to have healthy effects, and especially to be one of the best medicines against stress. Laughter therapies, "yoga" sessions or groups are emerging everywhere. Events connecting and entertaining people from all over the world through the universal signal of laughter are also successful, like the World Laughter Day or the Skype Laughter Chain [1].

In addition, the recent technological progress made the creation of a humanoid interface to computer systems possible. An Embodied Conversational Agent (ECA) is a computer-generated animated character that is able to carry on natural, human-like communication with users. In the last twenty years several ECA architectures were developed both by the research community (e.g. [2], [3]) and the industry (e.g. [4], [5]). Recent works focus on standardisation of the ECA architecture. SAIBA [6] is an international research initiative which main aim is to define a standard framework for the generation of virtual agent behaviour. It defines a number of levels of abstraction, from the computation of the agent's communicative intention, to behaviour planning and realization. There exist several implementations of the SAIBA standard, among others SmartBody [7], [8], BMLRealizer [9], RealActor [10] and EMBR [11].

Due to the growing interest for virtual machines modeling human behaviors, a need to enable these machines to perceive and express emotions emerged. Laughter is clearly an important clue for understanding emotions and discourse events on one hand, and, on the other hand, to manifest certain emotions and provide feedback to the conversational partners. In consequence, automatic laughter processing has gained in popularity during the last decades. However, laughter is a highly variable signal and it is hard to acoustically describe its structure. Trouvain [12] summarizes the different terminologies used in other laughter studies, as well as various categories to designate laughter types. If a few systems able to distinguish between laughter and speech have recently been built on the recognition side (e.g. [13], [14], [15]), automatic laughter synthesis is still inefficient. Interesting approaches have been explored to generate human-like laughters (e.g. [16], [17]), but perceptive tests have shown that the resulting laughters do not sound natural. They miss an important characteristic of human laughters: variability.

The AVLaughterCycle project aims at developing an audiovisual laughing machine, capable of recording the laughter of a user and to respond to it with a virtual agent's laughter linked with the input laughter. The hope is that the initially forced laughter of the user will progressively turn into spontaneous laughter. This system will help improving emotional displays of virtual agents, and will, by itself, be an interactive application to enjoy the benefits of laughter. The virtual agent, Greta [18], will not display synthesized laughter: on the audio side, she will play an appropriately selected laughter inside an audiovisual database, and simultaneously on the visual side, she will be animated using the facial data of the selected laughter, obtained through motion capture.

The paper will be organized as follows. Chapter II will present the softwares used during this project: Smart Sensor Integration for recording/annotating/analyzing laughters, MediaCycle to evaluate similarities between laughters, Greta for playing the output laughter and the commercial softwares to perform motion capture, ZignTrack and OptiTrack. Chapter III will focus on the creation and annotation of the audiovisual laughter database, inside which utterances are selected to animate Greta. The AVLaughterCycle application process and its methods for analyzing the input laughter, selecting an answering laughter and driving Greta accordingly will be described in Chapter IV. The upcoming evaluation of the system will be discussed in Chapter V. Finally, conclusions and future works will be presented in Chapter VI.

II. Presentation of the tools

Several important existing tools have been used in this project, as such or modified to fit our needs. In this Chapter, these tools will be presented separately. Their integration in the whole project will be described in Chapters III and IV.

A. Smart Sensor Integration (SSI)

Smart Sensor Integration (SSI) [19] is a software designed by the University of Augsburg to deal with multimodal signal recording and processing. It provides a Graphical User Interface (GUI) to start and stop a recording. Afterwards the recorded data can be visualized and annotated. Given an annotation it is possible to automatically extract features and train a model. The different modalities are automatically synchronized.

The GUI includes a dedicated space to present stimuli, which is useful for database recordings. The stimuli are presented via HTML pages automatically managed by the SSI application. Browsing through successive HTML pages supports two different modes: clicks by users or automatic page switch either after a predefined time or after a certain number of events detected in the recorded data (e.g. a certain number of laughs). As well as recording the data, SSI stores the stimuli sequence.

SSI integrates signal processing libraries. Recorded signals can be analyzed in real-time or offline. Features are defined in a Dynamic Link Library used by the SSI GUI. Every kind of signal processing algorithm can be implemented there. One can also define "triggers": functions that decide whether or not a signal segment should be further processed; for example, employing a Voice Activity Detection on an audio input to only process parts of the signal(s) where there is vocal activity.

Using the triggers, SSI pre-segments the data. Pre-labels can be assigned to the segments via the HTML stimuli manager: when, for example, a funny stimuli is presented and laughters are expected, we can specify to assign a "laughter" label to every segment that respects the trigger conditions. The SSI GUI enables to further annotate the recordings by adding/removing segments, refining their boundaries or change their labels.

Once data is annotated, classifiers may be trained to model the feature distributions of the different classes. SSI provides classifiers implemented in the Torch3D library: Hidden-Markov Models (HMMs), Gaussian Mixture Models (GMMs), k-Nearest Neighbours (kNNs), etc. The trained classifiers can be used to label new data (in real-time or not) and can also serve as triggers in the SSI processing chain.

To summarize, SSI provides convenient methods for multimodal database recordings, annotation, classification and processing. The different aspects are used in AVLaughterCycle and SSI is integrated in the system architecture. This first integration already provides satisfying results, but will also enable us to improve the AVLaughterCycle application by exploiting more of the SSI processing and classification capabilities in the future.

B. MediaCycle

MediaCycle is a software developed at the University of Mons and the Université Catholique de Louvain for browsing through multimedia libraries, in the Framework of NUMEDIART Belgian R&D program (www.numediart.org). It started by considering acoustic similarities only, in a project called AudioCycle [20], designed to ease the navigation inside a large audio loops libraries. The software computes acoustic features - characterizing musical properties of rhythm, melody and timbre - for each file in an audio loop database and then evaluates the similarities between loops through the distances between their feature vectors. A Graphical User Interface has also been designed to visualize the database: loops are grouped into clusters through a K-means algorithm; a reference loop is randomly selected and other loops are positioned around it according to their cluster belonging and similarities with the reference loop. This is illustrated in Figure 1. Tools to easily browse through the library are available such as playing any combination of loops, which are synchronized, reorganizing the database by selecting a new reference loop or changing the features weights, splitting again one cluster, etc.

AudioCycle has been extended to deal with visual content in a project called MediaCycle where image features where added. Methods for computing similarities between videos are also progressively implemented, as well as dedicated methods to process laughter, which received a particular attention in another subproject called LaughterCycle. The system can also be queried by laughing: it then places the incoming laughter in the database space and outputs the N most similar utterances.

In this project, the visual database organization provided by MediaCycle will not be used since the visual output is performed by Greta. Only the MediaCycle engines for organizing a database and computing similarities between objects will be integrated in AVLaughterCycle.

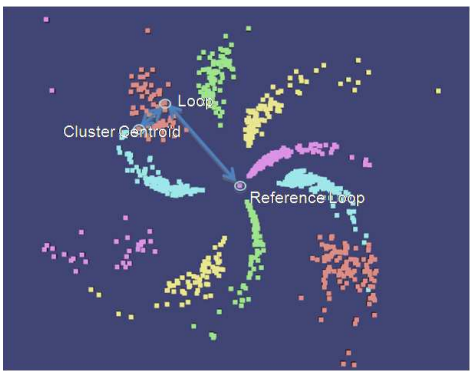

Fig. 1. AudioCycle Database visualization

C. Motion Capture

Motion capture (often referred to as "mocap") consists in recording a real motion by transcribing it under a mathematical form usable by a computer. This is achieved by tracking a number of key points through space across time, and combining them to obtain a tridimensional unified representation

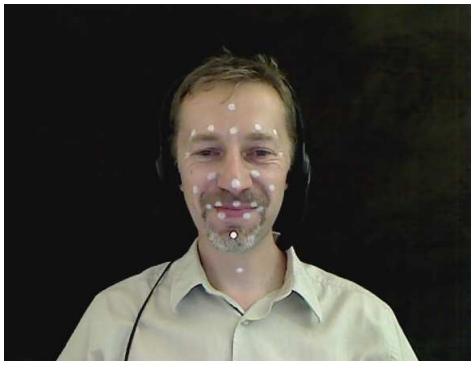

Fig. 2. ZignTrack - 22 markers on the subject's face

of the performance [21]. Several techniques can be used for motion capture, but when it comes to facial motion capture, only techniques that do not need intrusive equipment nor large markers can be considered.

Facial motion capture can be divided into two main types: marker and markerless techniques. While markerless techniques have the huge advantage that they can usually be performed on facial videos recorded without any specific setup, they are nowadays not robust enough to ensure automatic and reliable capture of the small variations of facial expression during laughter for instance. Using markers placed on the face eases the tracking and increases its robustness. However, the recording must then be performed in an unnatural setting, and very often with dedicated equipment and quite heavy setups.

In this project it was chosen to record our database using marker based tracking, in order to obtain data with as much precision and information as possible. Two different commercial motion capture tools, ZignTrack and OptiTrack, have been tested and used. They are presented below.

- **ZignTrack [22]** is the first software we used. It captures 3D facial motion with one single camera. It requires 22 facial features, marked with simple stickers or make-up (no special markers or infrared equipment required), as illustrated in Figure 2. They must be not too small, to be obvious on the video, nor too big, to track accurately the face features. ZignTrack handles head rotation, jaw/lip-syncing, eyebrows, eyelids sneer and cheek movements. As the subject is recorded with one single camera placed in front of him, the markers are actually tracked in a two dimensional space only, and the 3D points are extrapolated by the software using a fixed face template. The transformations linked to the head displacements and rotations are not all perfectly handled by the software, as we noticed for instance that the face was "shrinking" or "inflating" when there were up and down rotations of the head.
  Once the recording is over, the video is imported into ZignTrack, the face markers are manually linked to a template on the first video frame, and the tracking of those markers is then automatically performed. In case of tracking errors, manual tuning of each marker position can be performed to adjust/correct the automatic tracking. Once the tracking is done, ZignTrack extrapolates the 3D positions of the tracked face points. The resulting motion capture data can then be exported to several motion capture formats: BVH, TRC, Poser pz2 and Animation:Master action files. The ZignTrack software costs around 130 euros.
- **OptiTrack [23]** is an Optical Motion Capture solution developed by Natural Point. Our seven-cameras face motion tracking desktop setup is shown in Figure 3 (the positions of the 7 cameras are marked by a red circle).

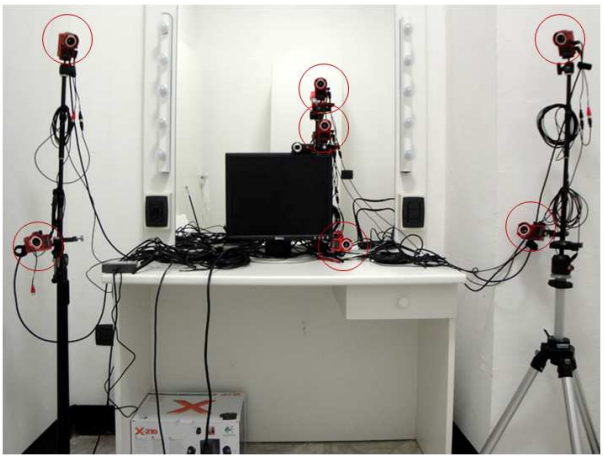

Fig. 3. Desktop setup for facial motion tracking using OptiTrack

  The seven synchronized infrared cameras are placed in a semi-circular way: six for face motion capture and a middle additional one for scene A/V recording (recording synchronized audio and video tracks for each take). For each of them, a grayscale CMOS imager captures up to 100 frames per second.
  OptiTrack requires at least 23 face markers and 4 head markers on the actor (Figure 4). These markers are infrared reflectors sticked on the skin, smaller than the white make-up dots of the ZignTrack device. Therefore they provide a very accurate and robust (versus head movements) face tracking using OptiTrack Arena Facial Expression software. The results can be exported to various formats such as BVH and C3D.
  The whole OptiTrack desktop setup is much more expensive than ZignTrack, and costs around 5000 euros. OptiTrack is not limited to face motion tracking but can be upgraded to cover full body motion tracking, by adding more cameras and sensors.

D. The 3D humanoid agent: Greta

Greta [18] (Figure 5) is a 3D humanoid agent developed by Telecom-ParisTech. She is able to communicate with the user using verbal and nonverbal channels like gaze, facial expressions and gestures. It follows the SAIBA framework [6] that defines a modular structure, functionalities and communication protocols for Embodied Conversational Agents (ECAs). Moreover, Greta follows the MPEG4 [24] standard of animation. Greta uses the FML-APML XML-language [25] to specify the agent's communicative intentions (e.g., its beliefs,

Fig. 4. OptiTrack - 23 face markers and 4 head markers on the subject

emotions) that go along with what the agent wants to say. The communicative intentions of the listener are generated by the Listener Intent Planner while the intentions of the speaker are defined at the moment manually in an FML-APML input file. The Behavior Planner module receives as input the agent's communicative intentions written in FML-APML and generates as output a list of signals in BML language. BML specifies the verbal and nonverbal behaviors of the agent [6]. Each BML tag corresponds to a behavior the agent has to produce on a given modality: head, torso, face, gaze, gesture, speech. These signals are sent to the Behavior Realizer that generates the MPEG4 FAP-BAP files. Finally, the animation is played in the FAP-BAP Player. All modules in the Greta architecture are synchronized using a central clock and communicate with each other through a whiteboard. For this purpose we use Psyclone messaging system [26] which allows modules and applications to interact through TCP/IP. The system has a very low latency time that makes it suitable for interactive applications.

Fig. 5. Greta, the 3D humanoid agent used in AVLaughterCycle

III. Creation of an AV laughter corpus

The first step of the AVLaughterCycle project is the recording of an audiovisual (AV) database consisting of humans laughing. Participants of the eNTERFACE09 workshop who wanted to contribute to this experiment were invited to laugh in front of the set of cameras. This Chapter is intended to describe the laughter database. It is divided in 7 sections presenting: the selection of stimuli and instructions given to the participants (Section III-A), the settings for audiovisual recording (Section III-B) and facial motion capture (Sections III-C and III-D), the corpus annotation protocol (Section III-E), the participants (Section III-F) and, finally, the database contents (Section III-G).

A. Elicitation method: selection of stimuli, protocol of DB recording

It is known that there is a difference between the expressions of real and acted emotions (e.g. [27]). To collect a corpus representative of humans' natural behaviours, one should try to capture the data in a natural environment, the subjects being unaware of the database collection until the end of the recording. Laughter being an emotional signal, it is affected by the same phonomenon: one cannot expect natural laughter utterances by simply asking subjects to laugh. To find spontaneous laughter utterances, it is popular to take the laughters recorded while collecting data for another purpose. For example, [13], [14] and [28] use the ICSI Meeting Corpus [29], recorded for studying speech in general by placing microphones in meeting rooms. Apart from speech, this corpus contains a significant number of laughters, which are assumed spontaneous since they occurr in regular conversations (even though the participants knew there were microphones). When for some reason natural data cannot be used, it is common to try to induce laughter - and not tell laughter is the object of the study - rather than asking to laugh. One way to achieve it is to display a funny movie.

In our case, both audio recording and accurate facial motion tracking were needed. To our knowledge, there existed no laughter database providing these 2 signals. Due to the markers required for facial motion tracking and the fact that subjects should stay in the camera(s) space, a natural laughter recording was impossible. To push the participants towards spontaneous laughter, even though they knew that they were being recorded, a 13-minutes funny movie was created by the concatenation of short videos found on the internet. The participants were asked to relax, watch the video and enjoy it. They could close their eyes, move a bit their head but should keep it towards the camera during the whole recording. Moreover, they could not put anything between their head and the webcam (e.g. hands), else the face tracking is lost. Except these two limitations, they could act freely, talk, laugh, cry, shake their head, etc. as they would do if they were at home. At the end of the experiment, subjects were instructed to perform one acted laughter, prentending thay had just heard/seen something hilarious.

B. Audiovisual (AV) laughter database recording

The AV laughter database was recorded on site (Casa Paganini, Genova, Italy), using one webcam (ZignTrack) plus seven infrared cameras (OptiTrack) for video recording, a

headset for audio recording (16 kHz, 16 bits/sample) and stimuli listening, and University of Augsburg's Smart Sensor Integration tool (SSI) for stimuli playing and audio/video recording synchronization (and later for recordings annotation). All these components have already been described in Chapter II.

C. Facial motion capture using ZignTrack

The webcam used has a 640x480 resolution, stores in RGB 24 bits and captures 25 frames per second (FPS). The 22 marker dots were simply made of white make-up (Figure 2). Another attempt was performed using red markers but the face tracking failed because of the poor contrast between them and the skin colour.

ZignTrack is a cheap facial motion capture software, working quite well with markers that stay visible during the whole recording and with slow head movements (fuzzy effect due to the 25 FPS limitation in case of fast head movements). If at least one of these constraints is not respected, the tracking fails, requiring heavy manual corrections. This is the reason why we turned towards a more sophisticated (and more expensive) system, OptiTrack.

D. Facial Motion Capture using OptiTrack

During this work, the seven-cameras Face Motion Tracking desktop setup shown in Figure 3 was used. Compared to the basic OptiTrack system, our setup also includes the webcam in parallel in order to be able to use the SSI software and keep all its previously explained advantages. A post-processing is carried out to synchronize the webcam with the OptiTrack cameras.

The OptiTrack Arena Facial Expression software performed very well and provided a more robust tracking than ZignTrack. Indeed, even if some markers are lost during the tracking (e.g. too large head rotations), they are nearly always recovered after a short period of time, thanks to the number of cameras and points of view (six) as well as to infrared (versus visible spectrum) acquisition performance. In addition, each individual marker can also be manually tuned to adjust/correct the automatic tracking if it does not recover by itself.

However, it seems that recordings longer than 5 minutes are not always completely saved (the end is sometimes missing). We thus decided to reduce the 13-minutes funny movie to 10 minutes, and to split it into 3 parts of around 3 minutes each.

E. Database Annotation

The recorded data have been annotated using SSI. A hierarchical annotation protocol was designed: segments receive the label of one main class (laughter, breath, verbal, clap, silence or trash) and "sublabels" can be concatenated to give further details about the segment. The main objective of the sublabels is to distinguish between different kinds of laughters, but still being able to rapidly group subclasses when needed, for example when only the main classes are relevant. Laughter sublabels characterize both:

- the laughter temporal structure: following the three segmentation levels presented by Trouvain [12]. These sublabels indicate whether the *episode* (i.e., the full laughter utterance) contains several *bouts* (i.e. parts separated by inhalations), only one, or only one syllable.
- the laughter acoustic contents: through labels referring to the type of sound: voiced, breathy, nasal, grunt-like, hum-like, "hiccup-like", speech-laughs or laughters that are mostly visual (quasi-silencious).

While only one main class can be assigned to a segment, sublabels can be combined, for example to indicate that the laughter episode contains several bouts and that we can find hiccup-like and voiced 'a' parts in it. To cope with exceptional classes conflicts that might influence the classes models when training a classifier - for example when we can hear a phone ringing in the middle of a laughter episode - a 'discard' main class has been added.

The annotation primarily relies on the audio, but the video is also looked at, to find possible neutral facial expressions at the episode boundaries or annotate visual-only laughters. In addition, laughters are often concluded by an audible inspiration, sometimes several seconds after the laughter main part. When such an inhalation, obviously due to the preceding laughter, can be found after the laughter main audible part, it is included in the laughter segment.

The annotated laughters form our laughter database, inside which an answering laughter is selected when AVLaughterCycle is queried (see Chapter IV).

F. Participants

24 subjects participated in the database recordings: 8 (3 females, 5 males) with the ZignTrack setting and 16 (6 females, 10 males) with the OptiTrack setting. They came from various countries: Belgium, France, Italy, UK, Greece, Turkey, Kazakhstan, India, Canada, USA and South Corea. The male average age was 28 (standard deviation: 7.1) and the female average age was 30 (sd: 7.8), which correspond to a global average age of 29 (sd: 7.3). All the participants gave written consent to use their data for research purposes.

G. Database contents

Annotation (Section III-E) is still under way, but from the 20 files that are already fully annotated, preliminary analyses of the corpus contents can be performed: subjects spend, in average, 23.5% of the recording laughing, which is a huge amount of time. The number of laughter episodes per participant stands around 43.6, with extreme values of 17 and 82, for a total of 871 episodes in these 20 files. The average duration of a laughter episode is 3.6s (standard deviation: 5.5s). A histogram of the laughters durations and their cumulative distribution function is presented in Figure 6. The large majority (82%) of the laughter episodes lasts less than 5s, but longer episodes should not be neglected as they represent 53.5% of the total laughters duration and, above all, are the most striking ones. The longest giggle in the analyzed database lasts 82s.

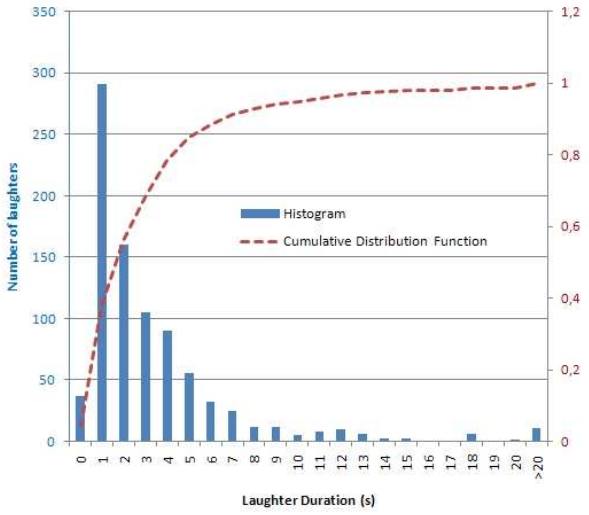

Fig. 6. Histogram and cumulative distribution function of the laughters durations

IV. Corpus based AudioVisual Laughter synthesis

The communications between the different modules are illustrated in Figure 7. The dashed arrows refer to the database building process. In this Chapter, the AVLaughterCycle application process will be described (solid arrows). Users can query the AVLaughterCycle systems in two ways: by sending a full audio laughter file (offline mode) or in real-time (online mode), using SSI for recording and real-time processing (with a trigger to delimit laughter segment boundaries). In both cases, when the audio laughter segment is available, SSI computes the segment features (see Section IV-A) and sends them to MediaCycle. MediaCycle compares these features with the database samples and outputs the most similar example, as reported in Section IV-B. This output is sent to Greta who plays the audio sound synchronously with the corresponding facial animation. To do so, Greta had to be slightly modified. This will be explained in Sections IV-C and IV-D.

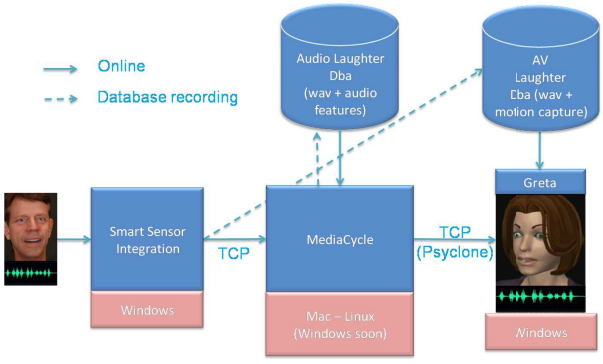

Fig. 7. Flow chart of the AVLaughterCycle application

A. Laughter audio similarity analysis

The labeled laughter segments are all processed by the MediaCycle tool to compute their similarities and cluster them. MediaCycle evaluates the similarities by measuring distances between feature vectors. Features have been based on Peeters' set [30] and implemented in a C++ library. The features can be extracted directly in SSI, where the MediaCycle audio feature extraction library has been integrated, and then sent to MediaCycle. In the current demo version, we used the following spectral features:

- 13 Mel-Frequency Cepstral Coefficients (MFCCs), their deltas and delta-deltas
- The spectral flatness and spectral crest values, each divided in 4 analysis frequency bands (250Hz to 500Hz, 500Hz to 1000Hz, 100Hz to 2000Hz and 2000Hz to 4000Hz).
- The spectral centroid, spread, skewness and kurtosis
- The loudness, sharpness and spread, computed on the Bark frequency scale
- The spectral slope, decrease, roll-off and the spectral variation

In addition, 2 temporal features were used: the energy and the zero-crossing rate. In total, 60 features were extracted for each frame of 213ms, with 160ms overlap. The similarity estimation requires comparing audio segments of different lengths, hence different numbers of frames. To obtain a constant features vector size, we decided to store only the mean and standard deviation of each feature over the whole segment. More complex models could be investigated but this simple transform already provides promising results. It had been successfully used in other similarity computation contexts [20] and was assumed applicable to laughter timbre characterization.

Euclidian distance between feature vectors is used to compute the dissimilarity between laughter episodes. For the moment, the similarity analysis involves only audio timbre features. It is planned to include audio rhythmic features, for which most of the algorithms are available in MediaCycle but processing of some exceptional cases should be improved to avoid unexpected behaviours in uncontrolled conditions (real-time use). Furthermore, visual features could be added to the similarity measures in the future, to take an audio-visual similarity decision. MediaCycle provides image/video feature extraction methods that could be used. Furthermore, the weighting of the different feature sets can be defined and modified in real-time by the user, to put the focus more on audio rhythm or video features, for instance.

B. Answering laughter selection

When AVLaughterCycle is queried, the input laughter is analyzed and his feature vector is computed. This vector is used to select a corresponding answering laughter inside the laughter database organized by MediaCycle. In this project, it was decided to output the closest (i.e. most similar according to our feature set) laughter from the input laughter. Doing this way, the system can be employed to search inside the database for a specific kind of laughter. However, other selection processes can be imagined to enhance a laughter interaction: the natural way of joining somebody laughing is probably not to mimic him. Further research could be made on humans' laughter interactions to determine how

we join laughing partners, model it and integrate that into MediaCycle's best answering laughter selection.

C. Visual Replay

The data from the motion capture softwares contain, for each frame, the position of each marker in the 3D space. Thus values for face are influenced by head rotations and body movements. First of all, these movements, used to animate Greta's general posture (with BAPs), were separated from the facial movements. Noise caused by the technical flaw of the capturing hardware was also removed. Such a data was used to animate Greta agent that uses MPEG-4 standard of animation. In this standard, the face model is animated by using 66 points called FAPs. Each of them deforms one region of the face in one direction (i.e. horizontal or vertical). Two different mappings were created to map the motion capture data, coming from ZignTrack or OptiTrack, to FAPs standard. Unfortunately many FAP points do not correspond to any marker. Thus it was not possible to use simple one-to-one mapping. For several FAPs, linear combinations of several markers values and weights were defined. Last but not least the motion capture data stored in the laughter database correspond to different face geometries of different subjects while our virtual agent uses only one face geometry model. Thus the captured movements of different persons (e.g. widely open mouth) had to be adapted to Greta's model. For this propose the mappings can be parameterized to cover the inter-personal variability.

D. GRETA is playing the analyzed facial signals from triggered AV laughter selected from the database

For the AVLaughterCycle application, Greta underwent certain modifications. Greta's behaviour is usually defined in BML language. It specifies the verbal and nonverbal behaviours of the agent. Each BML tag corresponds to a behaviour the agent produces on one modality: head, torso, face, gaze, gesture, speech. Single nonverbal behaviours are defined using high level symbolic representation. On the other side our laughter database contains the precise, frame-by-frame descriptions of partial animations (i.e. only the face) in FAP format.

In this project, the default BML syntax was extended to allow mixing (high level) BML commands with (low level) FAPs description and we modified Greta's animation engine to be able to generate a smooth animation for such a mixed content. Consequently Greta may display a laughter animation using the data from the laughter corpus which is accompanied by an audio file and other nonverbal signals that might be specified in BML language (like gestures, or other facial expressions). Greta was integrated in the AVLaughterCycle architecture using Psyclone and BML commands. It allows for immediate visualization of audiovisual response to user's detected laughter.

V. Evaluation of laughter synthesis based on laughter similarity

In order to assess the validity and efficiency of the developed laughter analysis and synthesis chain, an evaluation study will be carried out. The objective is to measure the similarity of the audio answer as well as the improvement brought by the visual display. The protocol will be the following.

To assess the similarity algorithm, subjects will be presented laughters by pairs and will be asked to rate their similarities on a Likert scale (1 to 7). The laughter pairs will be formed the following way: an input laughter will be selected to query the MediaCycle device, which will output 3 laughters: the most similar one, the least similar one and an average distance laughter; three pairs will then be constituted, each one gathering the input laughter (unmodified) and one of the MediaCycle outputted laughters. The same process will be repeated with a number (at least 10) of input laughters and the pairs will be randomly ordered for each subject.

To measure the improvement brought by the visual display, three different conditions will be tested: using audio only, using video only and combining both modalities. When video is used, it consists in a Greta animation driven by the corresponding laughter facial animation. Due to the number of pairs to compare, it is planned to have 3 sets of subjects and assigning each group to only one modality. At least 10 subjects will be needed in each group.

Mixed Anova tests will be performed to evaluate whether the most similar output of MediaCycle is indeed perceived as closer from the input laughter than the 2 other inputs (least similar and average distance) as well as looking to the differences across conditions.

VI. Conclusion

AVLaughterCycle, a software for real-time recording of laughter and playing of an acoustically similar laughter by an Embodied Conversational Agent, has been presented. The main deliverables of the project are the large audiovisual laughter database, that will be released fully annotated, and the integration of several different modules into one single processing chain to implement all the steps from laughter recording to similar output playing. Several issues were encountered during the project. We can cite communication bugs between SSI and MediaCycle, difficulties of automatic Facial Tracking during laughter or mapping from Motion Capture Data to Greta animation. Solutions were proposed for these issues during the project. Demos shown encouraging results but also revealed some lack of robustness in the similarity computation, which is the main focus for future developments. An evaluation of the device will be carried out in order to numerically characterize its efficiency. Means to automatize or ease the mapping between the motion capture data and Greta's animation will also be investigated. Other suggested future works include voice/character conversion (to avoid having one single agent laughing with different voices), integration of visual features in the similarity computation and building models to not only reproduce but synthesize laughter, as well as to imitate how humans respond to conversational partners' laughters.

Acknowledgments

The authors would like to thank all the eNTERFACE'09 attendants who participated in the creation of the database.

This project was partly funded by the Ministry of Région Wallonne under the Numediart research program (grant $N^0716631$) and by the European IP 6 project Callas. J.Tilmanne receives a PhD grant from the Fonds de la Recherche pour l'Industrie et l'Agriculture (F.R.I.A.), Belgium.

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Elisabetta Bevacqua is a post-doc at the Telecom ParisTech. She obtained her PhD at the University Paris 8 in 2009 and her Master in Computer Science at the University of Rome "La Sapienza" in 2002. Her main research interest is on the creation of embodied conversational agents, computer animation, co-articulation model for ECA, listener model.

Thierry Dutoit graduated as an electrical engineer and Ph.D. in 1988 and 1993 from the Faculté Polytechnique de Mons, Belgium, where he is now a full professor. He spent 16 months as a consultant for AT&T Labs Research in Murray Hill and Florham Park, NJ, from July, 1996 to September, 1998. He is the author of three books on speech processing, text-to-speech synthesis and signal processing, and the coordinator of the MBROLA project for free multilingual speech synthesis. T. Dutoit was an Associate Editor of the IEEE Transactions on Speech and Audio Processing (2004-2006) and a member of the INTERSPEECH'07 organization committee. He was the initiator of eNTERFACE workshops and the organizer of eNTERFACE'05. He also is the scientific coordinator of the Belgian NUMEDIART research program (www.numediart.org) for media art technologies.

Alexis Moinet holds an Electrical Engineering degree from the FPMs (2005). He did his master thesis at the T.J. Watson research Center of IBM (2005). He is currently working as a PhD student in the Signal Processing Lab of the FPMs. He is particularly interested in audio, speech and music processing.

Radoslaw Niewiadomski received the PhD degree in Computer Science in 2006 from the Universita degli Studi di Perugia, Italy. Currently he is a post-doc at the Telecom ParisTech. His research interests include nonverbal communication and expressions of emotions by an ECA.

Catherine Pelachaud is a Director of Research at CNRS in the laboratory LTCI, TELECOM ParisTech. She received her PhD in Computer Graphics at the University of Pennsylvania, Philadelphia, USA in 1991. Her research interest includes representation language for agent, embodied conversational agent, nonverbal communication (face, gaze, and gesture), expressive behaviors and multimodal interfaces. She has been involved in several European projects related to multimodal communication (EAGLES, IST-ISLE) and to believable embodied conversational agents (IST-MagiCster). She participated to the Network of Excellence HUMAINE and coordinates the workpackage entitled emotion in interaction. She is currently participating to the STREP SAMAINE, IP CALLAS and NoE SSPNet projects.

Benjamin Picart graduated as an electrical engineer (Telecoms & Multimedia) from the Faculté Polytechnique de Mons (FPMs), Belgium, in 2009. He performed his Master Thesis within Idiap Research Institute (Switzerland) in the field of Automatic Speech Recognition. His research interests focus on signal processing theory and its applications to speech processing.

Joëlle Tilmanne holds an Electrical Engineering degree from the Faculté Polytechnique de Mons (Belgium) since June 2006. She did her master thesis in the field of sleep signals analysis, at Lehigh University (USA). She is pursuing a PhD thesis in the TCTS (Circuit Theory and Signal Processing) Lab of FPMs since september 2006, in the field of HMM based motion synthesis.

Jérôme Urbain graduated as an electrical engineer from the Faculté Polytechnique de Mons (FPMs), Belgium, in 2006. He is currently PhD student at the Signal Processing and Circuit Theory (TCTS) Lab of the same University, working on speech processing in the framework of FP6 IP CALLAS. He is focusing on the acoustic aspects of laughter modeling, synthesis and recognition.

Johannes Wagner graduated as a Master of Science in Informatics and Multimedia from the University of Augsburg, Germany, in 2007. He is currently PhD student at chair for Multimedia Concepts and Applications Lab of the same University, working on multimodal signal processing in the framework of FP6 IP CALLAS. He is currently developing a general framework for the integration of multiple sensors into multimedia applications called Smart Sensor Integration (SSI).

Multimodal monitoring of the behavioral and physiological state of the user in interactive VR games

Dimitris Giakoumis, Athanasios Vogiannou, Ilkka Kosunen, Dieter Devlaminck, Minkyu Ahn, Anne Marie Burns, Fatemeh Khademi, Konstantinos Moustakas, Dimitrios Tzovaras

***Abstract*— This is the eNTERFACE 09 Project 1 final report. Within this project two experiments were conducted using the same experimental setup. This consisted of a VR "Labyrinth" game and a biosignals monitoring system. The first experiment aimed to compare gameplay features and challenges with "purely" technical game parameters like graphics and sound. The second experiment focused on the identification of psychophysiological and behavioral correlates of the changes in the user's affective state during repetitive tasks in HCI. During the workshop, 21 subjects played different versions of the VR game repeatedly, while their EEG, EMG, ECG and GSR signals were monitored. Features were extracted from the collected data and analyzed. Statistically significant correlation to the ground truth data was found for some of the extracted features.**

***Index Terms*— Biosignals, Multimodal Monitoring, Affective Interfaces, Virtual Reality, Immersion, Drowsiness, Flow**

I. Introduction

THE application of Virtual Reality methods and tools into a variety of research fields and commercial solutions is a topic receiving large interest recently. The major benefit of virtual environments is the ability to easily immerse users into controlled simulations and monitor their behavior according to various parameters, which is otherwise difficult or even impossible to implement. These systems usually involve different modalities that need to robustly operate in real-time under the restrictions and the specifications of the same setup.

The evaluation of the user experience in Virtual Reality applications is a subject receiving much interest for at least 10 years now. The term presence [1], which generally refers to the sense of "being" into a virtual world, is now considered as a reliable measure of the level of immersion in VR worlds, even though there has been a long discussion among experts about the methods that can be used to quantify presence [2]. In the literature, these methods refer to questionnaires and semi-structured interviews [3], biofeedback information [4] and behavioral observations [5] during VR related tasks. Regarding the evaluation of gaming experience, the same methods have been recently employed in a similar manner in order to extract some initial indicative results [6][7].

However, the role of presence in typical games is not as significant as in VR systems since most video games are usually played in PCs and therefore the level of immersion is rather limited compared to the use of complex VR setups with HMDs, Caves and real-time tracking. On the contrary, what is of high interest in games is the level of entertainment and/or fun that the player experiences and not at which level s/he feels that the virtual environment is real. Therefore, new approaches have been introduced to describe the gaming experience and usually include immersion as one of the factors that affect the user [8][9]. The most notable of them is flow [10][11] which refers to a balanced feeling between frustration and boredom as the game progresses. Despite the fact that game flow is well-defined, the methods used to measure flow are primarily based on questionnaires and interviews [10] which are known to have a subjective bias [2].

Moving towards more objective methods for the assessment of the user experience, the development of automatic affect recognition systems based on features extracted from the user's monitored biosignals has attracted much attention recently. During the last years, several important attempts have been made towards this direction [37]. However this research area is still in its infancy and one may say that is still an under-explored field. Regarding video games, the development of systems that are able to assess affective states related to flow would be of great importance. A pre-requisite for the proper development of such systems is the extraction of appropriate

D. Giakoumis, A. Vogiannou are with the Informatics and Telematics Institute Centre for Research and Technology Hellas, 6th Km Charilaou-Thermi Str. 57001 Thermi-Thessaloniki, Greece and the Aristotle University of Thessaloniki (dgiakoum@iti.gr, tvog@iti.gr)

K. Moustakas and D. Tzovaras are with the Informatics and Telematics Institute Centre for Research and Technology Hellas, 6th Km Charilaou-Thermi Str. 57001 Thermi-Thessaloniki, Greece (moustak@iti.gr, tzovaras@iti.gr)

I. Kosunen is with Helsinki Institute for Information Technology Pilotti Building, Metsδnneidonkuja 4, 02100 Espoo, Finland (ilkka.kosunen@hiit.fi)

D. Devlaminck is at the Department of Electrical Engineering, Systems and Automation of the Ghent University, Technologiepark 913, 9052 Zwijnaarde-Gent, Belgium (dieter.devlaminck@ugent.be)

Minkyu Ahn is with Information and Communication Dept. in Gwanju Institute of Science and Technology, South Korea. (frerap@gist.ac.kr)

A. M. Burns is with the M2S Laboratory, UFR APS, Université de Rennes 2, avenue Charles Tillon, CS 24414, 35044 Rennes (anne-marie.burns@mail.mcgill.ca)

F. Khademi is with the Industrial Dept.in Tarbiat Modares University,Iran. (ftmhkhademi@gmail.com)

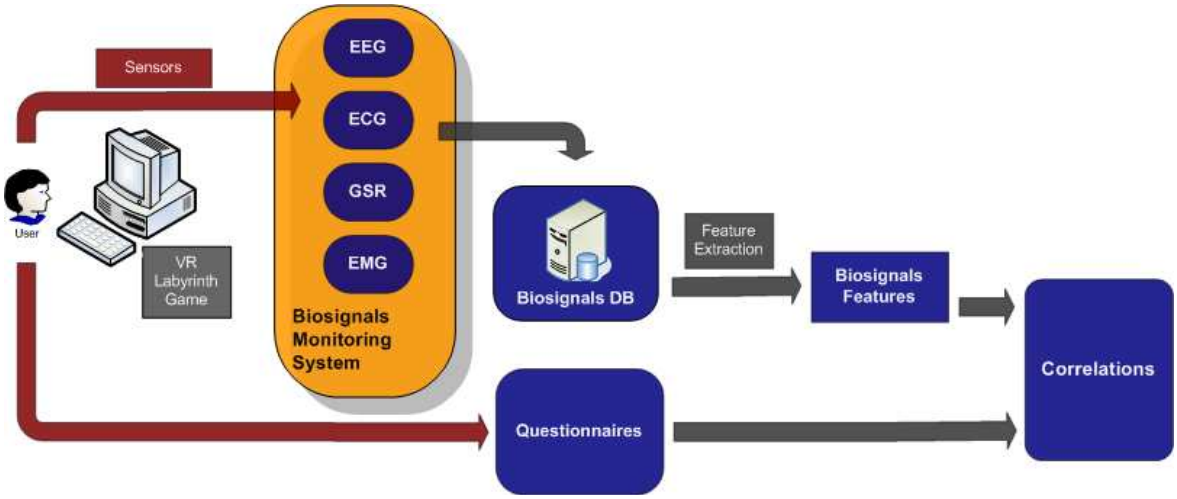

Figure 1. Project Overview

features from monitored biosignals, which correlate to the player's actual affective states of interest. These features can then be used in order to train appropriate classifiers, able to effectively classify the player's affective states.

Contribution: The main objective of this project was to work towards the development of a multimodal system for evaluating the level of immersion in games and VR applications and for measuring the psychophysiological impact of the gaming experience to the player. Special attention was paid on the transition of the user's affective state from an initial enjoyment - excitement to loss of interest - "drowsiness", caused from repetitive tasks during HCI.

II. Project Overview

During the eNTERFACE 09 workshop, two experiments were conducted, forming a single experimental session for the recording of biosignals from different modalities while subjects were playing a 3D labyrinth game. As shown in Figure 1, Electromyogram (EMG), Electrocardiogram (ECG), Galvanic Skin Response (GSR) and Electroencephalogram (EEG) were used to continuously monitor the state of the user. From the recording of these signals, the Project's Biosignals DB was populated. Using this DB, several features were extracted from the signals of each modality and analyzed, with the aim to identify correlations between them and the actual affective state of the subjects. The ground truth regarding the actual affective state of the subjects while playing the labyrinth game was formed from the analysis of the project's questionnaires, filled in by the players during the experimental session (Appendix A).

III. Monitoring Framework Modalities

As shown in Figure 1, the project's monitoring framework was based on the following biosignal modalities:

A. EEG

Electroencephalography (EEG) is the recording of electrical activity along the scalp, produced by the firing of neurons within the brain. Until now, lots of BCI systems have been developed on the basis of Electroencephalography, however, EEG has not been widely used for the assessment of the human affective state.

According to [20] there is one EEG measure that can be used to quantify one of the emotional dimensions. This particular dimension corresponds to the approach and avoidance behavior. Researchers discovered that this state can be quantified using frontal alpha asymmetry. Other works [17][18][19] investigating attention in human EEG relate alpha power changes with the level of attention in a target-response paradigm. Also, an increase in low frequencies and a decrease of high frequencies seems to be correlated with drowsiness as reviewed in [21]. Changes in theta rhythm seemed to be more prominent in the frontal regions while changes in alpha rhythm are more generalized. The use of ratios of theta, alpha and beta for assessing alertness was suggested by the authors of this work. Based on relevant findings already reported in the literature, in our study we considered several features extracted from the EEG modality, in order to identify statistical correlations between them and the changes in the actual subject's affective state.

B. ECG

For the purpose of our experiments, we used the ECG modality in order to extract features regarding the subject's Heart Rate Variability (HRV). Heart Rate Variability describes the variations between consecutive heartbeats. The regulation mechanisms of HRV originate from sympathetic and parasympathetic nervous systems and thus HRV can be used as a quantitative marker of autonomic nervous system [27]. Stress, certain cardiac diseases, and other pathologic states affect on HRV. Furthermore, features reflecting the HRV have already been used together with features derived from other modalities in a number of studies targeting automatic emotion recognition like [32] and [33]. A good review of physiological origins and mechanisms of HRV can be found in [28]. Generally, HRV analysis methods can be divided into time-domain, frequency-domain, and nonlinear methods.

The time-domain parameters are the simplest ones, calculated directly from the RR interval time series. These are

the time series produced from the time intervals between the consecutive "R-peaks" of the raw ECG signal. The simplest time domain measures are the mean and standard deviation of the RR intervals (IBI – Inter-beat Intervals). The standard deviation of RR intervals (SDNN) describes the overall variation in the RR interval signal.

In the frequency-domain analysis, power spectral density (PSD) of the IBI series is usually calculated. Methods for calculating the PSD estimate may be divided into nonparametric [e.g. fast Fourier transform (FFT) based] and parametric [e.g. based on autoregressive (AR) models] methods. The commonly used frequency bands for HRV are very low frequency (VLF, 0-0.04 Hz), low frequency (LF, 0.04- 0.15 Hz), and high frequency (HF, 0.15-0.4 Hz). The most common frequency-domain parameters include the powers of VLF, LF, and HF bands in absolute and relative values, the normalized power of LF and HF bands, and the LF to HF ratio. In our study, we extracted features from the IBI's time and frequency domains in order to examine their correlation to the user experience and affective state transitions.

C. GSR

Galvanic Skin Response (GSR), also referred to as Electrodermal activity (EDA), is a measure of skin conductance, which can be seen as an indirect measure of sympathetic nervous system activity [12]. The outer level of skin is highly resistive while the deeper layers of skin are highly conductive. These levels are "connected" by sweat glands, that when opened, create a pathway from the surface of the skin to the deeper, conductive level of the skin [13]. There are two kinds of sweat glands, apocrine and eccrine. Apocrine glands are the glands found in, for example, arm pits, and are what people normally consider as sweat glands. Eccrine glands are the most interesting ones, and are thought to correlate with sympathetic nerve activity. Eccrine glands are found around the body, but typical locations for practical measurements are the soles of the feet and the palms of the hand.

EDA measures the amount of skin conductance, which is positively correlated with eccrine gland activity which in turn is correlated with sympathetic nerve activity. These eccrine glands respond only weakly to certain level of heat (the normal sweating) and strongly to psychological and sensory stimuli. The sweating to psychological stimuli has sometimes been termed "arousal" sweating. There are two main types of fluctuations of EDA that occur with stimulation: the momentary phasic responses and the more stable tonic level.

GSR has been connected to "arousal" but the exact meaning of arousal is somewhat fuzzy. Some define arousal as the general increased activation of Sympathetic Nervous System. Some conceptualize it as "as something that describes the intensity of an experience but not its quality". Because EDA has been associated with several psychological processes, it has been criticized as not being a clearly independent measure of any particular psychological process [14].

In this study, we extracted a set of features from the GSR modality in order to identify correlations to the player's experience and affective state changes. As an initial hypothesis regarding "GSR and drowsiness", we have considered arousal to be diametrically opposed to boredom, but this definition of course cannot be absolute. For example, it is unclear whether the orienting response of EDA can be seen as indication of lack of boredom.

D. EMG

EMG stands for electromyography. It is the study of muscle electrical signals. Muscle tissue conducts electrical potentials similar to the way nerves do and the name given to these electrical signals is the muscle action potential. Surface EMG is a method of recording the information present in these muscle action potentials. Various signal-processing methods can be applied on raw EMG [29]. The most commonly used ones are based on the time-domain analysis of the rectified averaged or the RMS of the raw EMG signals.

There are many applications for the use of EMG. EMG is used clinically for the diagnosis of neurological and neuromuscular problems. It is used diagnostically by gait laboratories and by clinicians trained in the use of biofeedback or ergonomic assessment. EMG is also used in many types of research laboratories, including those involved in biomechanics, motor control, neuromuscular physiology, movement disorders, postural control, and physical therapy. Moreover, EMG has been used several times to study expressive aspects of emotions in HCI [30]. For example, Partala & Surakka [30] studied the effects of affective interventions. They recorded facial EMG responses from the zygomaticus major and corrugator supercilii muscle sites, that control smiling and frowning.

Moving away from facial electromyography, in our experiment, we tried to explore the evolution of the coordination of the player's muscles responsible for moving the mouse through trials and time. Our initial hypothesis was that the coordination between the agonist and antagonist muscles would change through trials and this could be indicative of changes in the user's affective state, when combined with features derived from the other modalities used.

IV. THE VR LABYRINTH GAME

A basic 3D labyrinth game was developed for the purposes of the project's experiments. In order to complete the game, the players had simply to find the exit.

Figure 2. Screenshot of the game version 1 (Graphics)

The player could walk through the mazy corridors of the labyrinth using a 3D first person camera which is controlled by the WASD/Arrow keys and the mouse, a standard method in commercial games. The game was developed in C++ using OGRE [34] for graphics, OpenAL [35] for sounds and the Bullet physics library [36] for physics simulation. The tests were performed on a Laptop PC with an Intel Core 2 Duo T7700@2.40GHz CPU, 2 GBs of RAM and a NVIDIA GeForce 8600M GT graphics card. The game ran steadily on a 60 frame/sec rate.

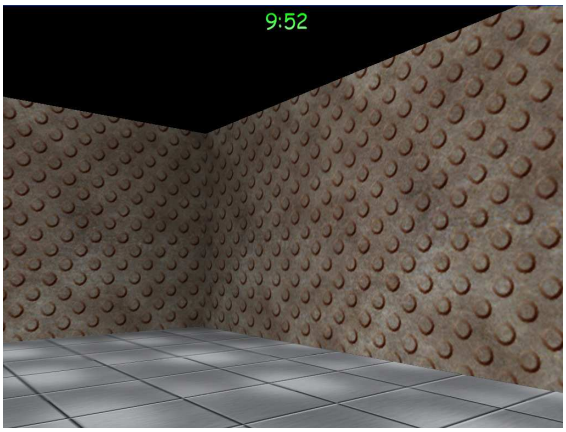

Figure 3. Screenshot of the game version 2 (Gameplay)

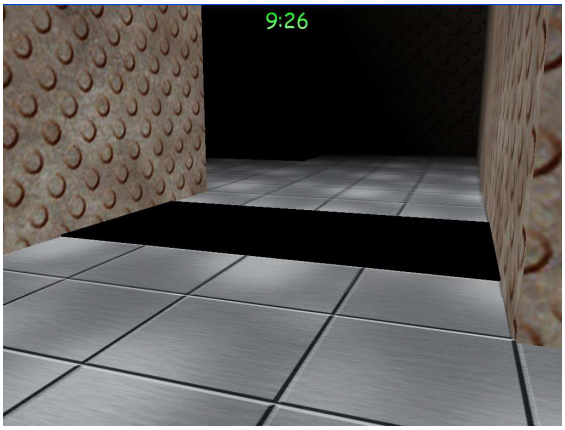

Figure 4. A «hole» game trap

Three different versions of this basic labyrinth game were developed. The first, Graphics version (Figure 2) displayed advanced real-time graphic techniques such as parallax mapping, dynamic lighting and particle effects (rain), as well as sound effects (footsteps, raindrops). However, this version lacked of any kind of gameplay features, leaving the player to just find the exit after wandering for a short time in the labyrinth. On the other hand, the second, Gameplay version (Figure 3) used much simpler graphical techniques but contained distinct gameplay features such as a time limit and death traps (Figures 4, 5) that would enable the user to think more while playing and have a more intense experience in order to win the game. The differences between versions 1 and 2 are summarized in Table 1. The third version developed combined the "low" features of the two previous games, namely low graphics rendering and a complete lack of challenges. This version was used to induce boredom after several repetitions,

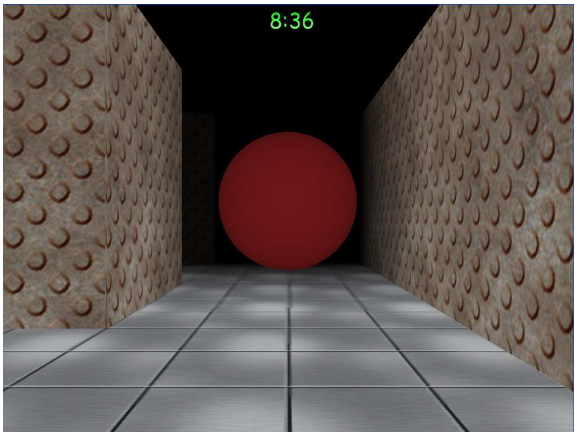

Figure 5. A «ball running towards the player» game trap

TABLE 1
DIFFERENCES BETWEEN THE TWO GAME VERSIONS

Game Feature	Version 1 (Graphics)	Version 2 (Gameplay)
Advanced graphics	YES (parallax and bump mapping, dynamic lighting)	NO
Sound Effects	YES (footsteps, raindrops)	NO
Particle Effects	YES (rain)	NO
Game Challenges	NO	YES (traps)
Time Limit	NO	YES (10 mins)
Checkpoints (if the player dies, she/he restarts from the last checkpoint)	NO	YES
Estimated time to finish game	1-2 mins	~5 mins

V. EXPERIMENTAL SETUP

The experimental setup was based on the project's biosignals monitoring system and the three different versions of the same labyrinth game developed. The project experiments along with the experimental setup used are described in this section.

A. *Project Experiments*

Two different experiments based on the same setup were conducted, focusing on different aspects of the VR experience:

1) *Experiment 1*

Experiment 1 focused more on the evaluation of the importance of gameplay features and challenges in comparison with the purely technical game parameters like graphics and sound. The aim of this experiment was to evaluate the gaming experience of a player in two different versions of the same

game, our developed 3D labyrinth. Besides the standard questionnaire based surveys that have been used in the past to define structural game characteristics and their effect to the gaming experience, this experiment employed psycho-physiological analysis from biofeedback information. Our goal was to provide a first quantitative result in the long debate of the game industry: "graphics vs gameplay?" which can be taken into consideration when designing commercial or educational games.

2) Experiment 2

In this experiment we tried to identify psychophysiological correlates of the human affective state of reduced attention and loss of concentration during human-computer interaction. One great challenge of affective computing is for computer systems to be able to identify whether the user has lost interest in the interaction, and thereafter adapt the interaction context properly in order to draw the user's attention again. A major cause of reduced attention and concentration is repetition; when a computer-system user is repeating the same actions again and again, it is very possible that s/he will lose interest in the interaction context, and thus stop paying attention to it. This can even become a very dangerous situation, when for instance referring to safety critical systems.

In the future, computer systems have to be provided with the ability to identify whether the user has lost interest and is not paying the required attention to the interaction. In this context, Experiment 2 was based on the concept of "repetition that causes loss of interest". In our particular situation, the subjects were asked to play the same simple (labyrinth) game repeatedly until they got tired of it and bored. By measuring a set of different biosignals (EEG, ECG, GSR and EMG) and monitoring their evolution through time during the experimental session, we tried to identify correlations between features extracted and the affective state of drowsiness, reduced attention and loss of concentration as reported in the questionnaire by the subjects.

B. Hardware setup

1) Sensors

For the purpose of the project's experiments we used:

a. Two three-electrode EEG sensors placed on the Fp1 and Fp2 positions of the 10/20 System (Figure 6).

Figure 6. EEG electrode placement

b. One three-electrode ECG sensor placed at the subjects' forearms, or in cases that the subject had very low cardiac pressure, on its chest (Figure 7).

Figure 7. ECG electrode placement

c. One two-electrode GSR sensor placed at the subject's ring and small fingers (Figure 8).

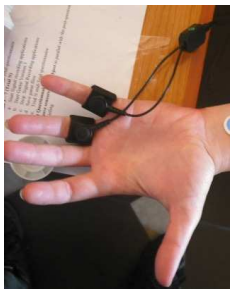

Figure 8. GSR electrode placement

d. Two pairs of autoadhesive Ag/AgCl bipolar surface electrodes (bandwidth 10-500 Hz, pickup surface 0.8 cm^2, inter-electrode distance 2 cm), to record the muscle activity of "Abductor Policis Longus" and "Flexor Carpi Ulnaris" (Figure 9).

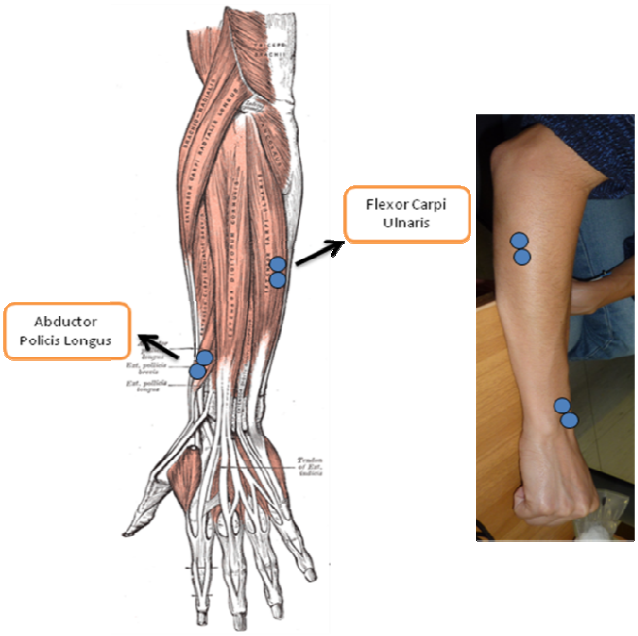

Figure 9. EMG electrode placement

2) Biosignals Monitoring Devices

The biosignals' monitoring system was mainly based on the Procomp5 Infiniti device. In particular, 2 EEG, 1 ECG, and 1 GSR sensors were connected on it. Furthermore, a second A/D device was used for the recording of the signals derived from the two EMG channels used (Figure 10). Both monitoring

devices were connected at the same PC. This was a Laptop PC with an Intel Core 2 Duo T7500@2.40GHz CPU, 2 GBs of RAM, a NVIDIA GeForce 8600M GS graphics card and Windows Vista Home Premium edition. The synchronization of the measurements was based on a custom-made application, while the two different PC's were synchronized on the basis of the Network Time Protocol (NTP).

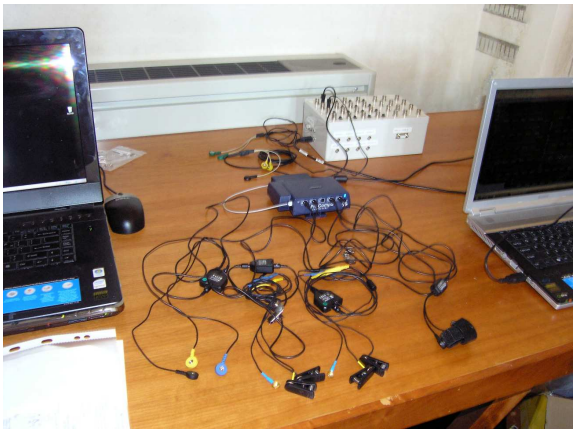

Figure 10. The Project's Biosignals Monitoring Devices

C. *Experimental protocol*

Experiments 1 and 2 were performed during a unique session due to the time required to install correctly the sensors on the subject. The entire experiment lasted for one to one and a half hour, half an hour of it being devoted to the sensors placement. Subjects were consequently advised to be ready for a one and a half hour session without possible interruption due to the cables linking them to the monitoring devices and computers. All subjects were informed that they could stop the experiment at any point without any consequences or questions, however every subject completed the entire experiment.

Initially, the subjects were asked to sign a consent form, to certify that they were not having any medical problem that could prevent them from taking part in the experiment and to specify if they were left or right handed. After that, one of the experimenters would start to install the sensors on the subject while another experimenter helped the subject to complete the pre-questionnaire. The purpose of the pre-questionnaire was to collect personal data on the subject and on his/her previous experience as a gamer for experiment validation purposes only.

Once the sensors were placed, the subjects were asked to relax with eyes-closed for one minute in order for the signal to stabilize (rest session). After this point, three reference captures were performed. The subjects would watch a boring and an entertaining movie for 2 minutes with a relaxation pause of 1 minute between the two movies in order to acquire some calibration data for drowsiness/boredom and attention. One of the movies displayed a fixed cross (boring movie) while the other movie contained first person scenes of extreme sports (interesting movie to elicit attention). The movies did not contain music in order to exclude emotions that could be induced from it.

In order to draw the subject's attention effectively we compiled the interesting movie on our own. This was a movie that none of the subjects had ever seen before as was done in [16]. We did not use the standardized database of pictures [15] as the pictures included were not rated for interest/alertness and are especially used to elicit emotions. Additionally, according to [16] subjects did pay less attention to pictures than to movies. The movie database given in [22] did rate the movies according to interest/alertness, however we were not able to download and use this database.

The two videos were presented in altered order between subjects; ten watched the attention movie first and eleven the boring one. The "data acquisition session questionnaire" served to confirm that the movies induced the desired emotion to the subjects.

The third reference capture was related to the calibration of the EMG signal recorded. For this purpose, the effect on the EMG of maximum isometric contraction to the left and to the right of the right wrist of the subject was measured at this point. This data was needed in order to normalize each subject's actual EMG signal, recorded while moving the mouse during playing the labyrinth game.

After all these measurements and another period of relaxation, the subject would start experiment one. Subjects were only informed on the way to control the game and on their objective to find the exit of the labyrinth; this information was also provided at the game start. Subjects would play either the Graphics or the Gameplay version of the game first. Eleven subjects played the Graphics version first and ten the Gameplay one. After each trial, subjects were asked to fill in the mid-trials questionnaire and to relax for one minute before starting the next game.

Once experiment one was completed, the subjects were presented with a third version of the game displaying low graphics and no challenges. After a period of relaxation, they would play the game repeatedly taking time to fulfill the questionnaire and one minute of relaxation between each trial. The experiment continued until the subject had played a minimum of ten trials and had signaled its boredom in the questionnaire at least two times in a row.

At the end of the two experiments, ten subjects were asked to play the Gameplay version again with the instruction to do the best time possible. This was done in order to observe if their inexperience with the game had influenced their first trial and if playing the challenging game again would reduce their amount of boredom. All subjects were also asked to fulfill the post-questionnaire, which was used for the collection of their impression on the entire experiments.

VI. Data Analysis

A. *Subject Statistics and behavioral analysis*

The experiments were performed on 21 subjects chosen among the participants of the eNTERFACE'09 summer workshop held in Genova, Italy from July 13th to August 7th 2009. Participants were from universities of seventeen different countries mostly from the European Union but also from North and South America, Asia and the Middle East

countries. Most participants were computer scientists or worked in the computer arts, media or technologies domains. Therefore, all participants frequently used computers in their work. Subjects were between 23 and 44 years old with 48 percent of them being 25 and 26 years old, 14 were males and 7 females, only one was left-handed but was using his right hand the move the mouse anyway.

Although 71 percent of the subjects claimed that at the present time they play an hour or less of video games per week, 81 percent of them reported to have five years or more of video game experience. Consequently, only four subjects (19 percent) had one year or less of game experience among which two claimed to have played only casual and educational games on extremely rare occasions. Also 42 percent of the subjects were already familiar with 3D maze but only four (19 percent) of them played this type of game frequently (more than one hour per week).

Game experience doesn't seem to interfere with the subject's ability to perform the task of playing the basic version of the game used for experiment two. In fact, in the course of the experiment, all subjects achieved a best time under 52 seconds with a maximum of two errors (ending in a dead end or going back to a path more than once). Moreover, 52 percent of the subjects were even able to complete the game doing a perfect path on one or more of their trials with an average completion time of 34 seconds. Among the four players who claimed to have less than one year of game experience, two were able to complete the game with a perfect path and a best time under the average on one or more of their trials, but the best time of the two others was over the average completion time of all subjects.

On the other hand, five subjects were unable to complete the version of the game including gameplay features used in experiment one. Three of them were among the declared inexperienced player as the two others claimed 5 and 10 years of gaming experience, one of them even mentioned having played 3D maze games before. One subject could not complete the game because he was unable to find the path, another managed to arrive to the end but missed the exit by a few seconds; three others were blocked by their inability to jump. It is important to note that all of them played this version of the game on their first trial. This implies that 46 percent of the subjects who were assigned this version on their first trial failed to complete it. Furthermore, three of them were asked to replay the Gameplay version of the game at the end of the second experiment and two of them succeeded with completion time and amount of errors under the average.

The difference in the gaming background is evident in the analysis of the questionnaires for the comparison of the two different game versions (Table 2). Subjects with at least 10 years of game experience and 1 hour of gaming per week are considered to be "Experienced" while the rest are considered to be "Novice". The increase in Flow (+0.8) and Positive Affect (+0.67) for experienced subjects strongly indicates a trend in favor of gameplay challenges. On the other hand, less experienced players do not show a clear preference between the two game versions. While Challenge is indeed increased for the second version (+1.46) this does not result in a significant increase in Competence or Flow as happens with experienced players.

Further analysis on the game and behavioral data showed that novice players felt rather frustrated and annoyed by the traps and the time limit, instead of regarding them as fun and enjoyable features of the game. This explains the inconclusive results on Flow, since these players would probably prefer much simpler and easier games, e.g. casual or educational games. Therefore it is clear that game characteristics have quite opposite affect on players with different gaming backgrounds.

TABLE 2
QUESTIONNAIRE SCORES FOR THE TWO VERSIONS OF THE GAME

	Experienced		**Novice**	
	Gameplay	**Graphics**	**Gameplay**	**Graphics**
Flow	3.9	3.1	3.35	3.32
Pos. Affect	3.73	3.06	3.1	3
Neg. Affect	1.56	1.93	1.96	2.07
Competence	3.83	3.17	2.57	3.14
Tension	1.67	2.7	2.25	2.64
Challenge	3.26	2.4	3.6	2.14

B. Biosignal Features Extraction and Analysis

1) Statistical Analysis Method

After preprocessing we ended up with 21 test subjects and over 70 features for each of the trials. All of this data was inputted into SPSS for statistical analysis. Correlations regarding Experiment 2 were calculated only for trials 3 to 10, to remove the first 2 trials (the Gameplay and the Graphics one) and also the trials beyond 10, since there were only few players with that many trials.

As an exploratory phase of the data analysis, non-parametric correlations (Kendall's tau) were calculated between the questionnaire data and the physiological data. Significance level was set at $p<0.05$ (*) and $p<0.01$ (**). Partly due to relatively large sample size, there were several statistically significant correlations ($p \leq 0.001$), but the correlation coefficient only a few times reached values higher than 0.25.

2) EEG modality

We investigated a number of features derived from the processing of the EEG signal:

- Theta, alpha and beta power (divided by total power), both for Fp1 and Fp2
- Theta/alpha ratio and theta/beta ratio, both for Fp1 and Fp2
- Alpha asymmetry

The features were computed in a 25 second long window, starting five seconds after the beginning of the game. One of the difficulties of processing the EEG signals in our case was the large number of eye blinks per trial. Eye-blinks are considered to be artifacts that could severely distort the results and thus we tried to remove them prior to the feature extraction. For this purpose, the aforementioned features were calculated and evaluated after applying the eye blink detection and removal algorithm explained in the following.

a. Eye-blink detection

Initially, the position of the eye blinks had to be detected. For this purpose, a cross-correlation method [23] was used. The EEG signal recorded during the "rest" session of each subject was used as a normal signal, without artifacts, since during the rest session, subjects had their eyes closed and consequently, the effect of eye-blinks was absent. To exclude noise of other sources we manually select a period of rest data without noise. To compute the cross-correlation coefficients a window of 128 samples was used. By moving this window and calculating the correlation coefficient for each of these windows, we were able to get an averaged value for this coefficient. This gives a threshold to determine in which window we have an eye blink. We considered the maximum amplitude of the window as a second condition for eye blink detection. This was done to exclude detection of other artifacts such as head movement and eye movement. The discrete cross correlation method was calculated with the formula:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \sqrt{(y_i - \bar{y})^2}}$$

The threshold was determined by averaging over 70 eye blinks across all trials of 5 subjects. The eye blink was chosen randomly from the start, middle or end of the trial. The start of the eye blink was marked 30 samples before the detected eye blink position and the end was marked 90 samples after.

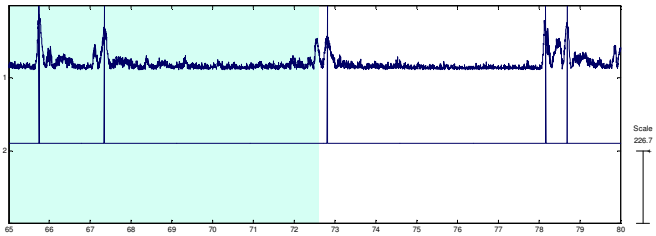

Figure 11. Raw EEG signal and Detected blink position using cross-correlation

b. Eye-blink removal

The most popular eye-blink removal techniques are based on independent component analysis (ICA) or principal component analysis (PCA). Generally, the ICA based method has been known to give the best performance. However, these studies use more EEG channels than the two we used. This makes it quite hard for ICA to completely separate the eye blinks from the neural information. Even if we find an eye-blink related independent component (EBIC), the recovered signals after deleting the EBIC, Fp1 and Fp2, are just a linearly scaled version from the remaining independent component. Therefore, we developed three methods:

- 1st method (Remove): Remove the eye-blink region of the signal.
- 2nd method (Filter): Filter the eye-blink region in the beta band.
- 3rd method (ICA): Filter the eye-blink region in the beta band of the EBIC and project the components back to the original signal.

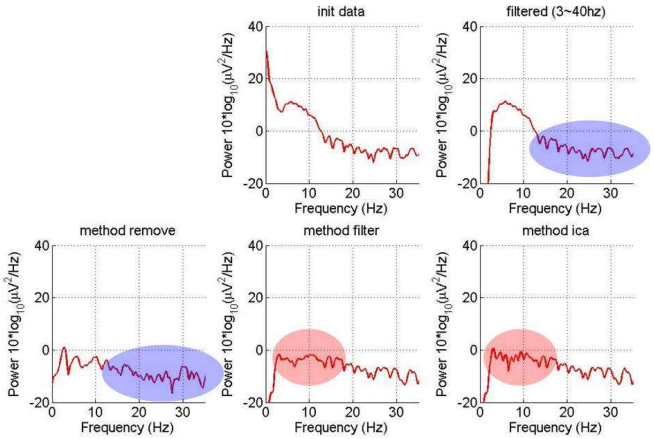

Figure 12. Power Spectral Density of Initial data, band-pass filtered(3~40hz), 1st method(remove), 2nd method(filter), 3rd method(ica)

Figure 12 shows the power spectral density associated with the three methods. The 1st method seems to affect the power in the beta region. In the second and third method we lose some information in the alpha and theta band, while information in the beta band remains unaffected. However, the 3rd method is a bit different from 2nd as we retain some extra information in the theta and alpha region during the eye blink, because some of the frequencies are still in the second independent component and are thus recovered. Therefore, we decided to use the last method for further feature extraction.

3) ECG modality

Regarding our project's ECG modality, we explored the potential of using three different features representative of the subject's Heart Rate Variability, which derived from the ECG IBI (Inter Beat Intervals): the "IBI Mean" and "IBI SD (Standard Deviation)" from the time domain (TD) and the "LF/HF (Low Frequency (0.014-0.15 Hz) power / High Frequency (0.15-0.4 Hz) power) Mean" from the frequency domain (FD). Our aim was to identify correlations between the features' evolution through time and the user's affective state changes. We extracted these features from the IBI data collected during the whole of each trial

Prior to the feature extraction, we removed IBI artifacts by applying a filter excluding IBIs over 1200 and under 500 ms. We decided to apply this filter, since an IBI under 500ms which is not an artifact means that the subject suddenly has a Heart Rate over 120 beats/minute and a not-an-artifact IBI over 1200ms means that the subject suddenly has a Heart Rate lower than 50 beats per minute.

Furthermore, in order to overcome difficulties imposed from the between-subjects variations within the features used, we normalized the extracted features to the minimum and maximum values retrieved from each subject by using the formula:

$$IBI_{norm} = \frac{IBI - IBI_{\min}}{IBI_{\max} - IBI_{\min}}$$

Where:

$IBI_{\max}$ = The maximum IBI value recorded for the specific subject in all trials

$IBI_{\min}$ = The minimum IBI value recorded for the specific subject in all trials

4) GSR modality

In this study, we measured both the tonic and phasic electrodermal activity. For the tonic EDA we initially calculated the sum of the GSR signal during a trial (sEDA). Then, tonic EDA was measured in three ways: as the amount of sEDA during a trial, divided by the trial length and normalized to the pre-exam baseline, as the amount of sEDA that was normalized to the pretrial resting period before each trial and divided by the length of the trial, and as the amount of EDA during the first 20s of each trial.

Three kinds of phasic features were extracted: the number of phasic responses during a trial, the average length of phasic responses during a trial, and the average amplitude of the phasic response during a trial. There are no clear rules of defining what constitutes a phasic response, but we used a measure of %5 increase of EDA during 1 second interval as an onset of phasic response. The 5% was measured from the range of EDA during that trial.

Furthermore, after applying a within-subject normalization of the mean EDA level per trial, we investigated this feature's alteration between the Gameplay and Graphics trials (by taking into account now only trials 1 and 2). In particular, for each subject, we normalized the GSR signal to the subject's minimum and maximum GSR values recorded, by using, similarly to the case of the ECG modality the formula:

$$GSR_{norm} = \frac{GSR - GSR_{\min}}{GSR_{\max} - GSR_{\min}}$$

Where:

$GSR_{\max}$ = The maximum GSR value recorded for the specific subject in all trials

$GSR_{\min}$ = The minimum GSR value recorded for the specific subject in all trials

Then, we calculated the average of the normalized GSR for all the Gameplay and all the Graphics trials of all subjects.

5) EMG modality

We tried to assess the agonist-antagonist muscle coordination by calculating the ratio between the average amplitude of the raw EMG's rectified average signal of the agonist muscle to the one of the antagonist, for each subject's mouse movement during each trial. Since all of our subjects used their right hand in order to move the mouse, for the right mouse movements, the agonist muscle was set as the Flexor Carpi Ulnaris and the antagonist was the Abductor Policis Longus. This configuration was inversed for left mouse movements.

For the purpose of our experiment we extracted a set of three features from the rectified average EMG signal. These were: "Right mouse movements Agonist / Antagonist muscle Ratios, averaged for each trial" (EMG_AvgRatiosR), "Left mouse movements Agonist / Antagonist muscle Ratios, averaged for each trial" (EMG_AvgRatiosL), "All mouse movements Agonist / Antagonist muscle Ratios, averaged for each trial" (EMG_AvgRatiosA). In order to calculate these features, first we had to identify the time window for each (right or left) mouse movement and then to calculate the average ratio of the agonist-antagonist signal amplitudes for each window. Finally, for each trial, we calculated the average of these ratios. In order to overcome the between-subjects variations in our analysis, prior to the feature extraction, we normalized all data collected from each subject's muscle to the corresponding maximum values taken from the maximum isometric contractions conducted at the beginning of each session.

VII. Results

As explained in the Data Analysis section, in order to identify correlations between biosignal features and the subject's actual affective state (as this had been indicated within the mid-trials questionnaires), a set of features for each of the modalities used was analyzed on the basis of the Kendall's tau correlation coefficient. Several statistically significant correlations (below the 0.001 level of significance) were identified. In the following, the most significant of them regarding each modality are summarized.

A. ECG

First of all, as shown in Table 3, a statistically significant correlation was identified between the IBI Mean value per trial and the question indicating the subject's drowsiness (Q3), τ=0.258 (p=0,001). This positive correlation of the IBI Mean per trial with the subject's drowsiness was an expected result, since higher Inter Beat Intervals mean decreased heart rate, a feature indicative of low arousal and drowsiness according to the literature.

The IBI Mean per Trial value was also found to be negatively correlated with the question indicating the subject's level of concentration to the game (Q5). In particular, as shown in Table 3, these variables demonstrated a Kendall correlation coefficient value of τ=-0.176 (p<0.001). This result indicated that during the trials that the subjects were more concentrated; their heart rate had the tendency to be increased.

TABLE 3
STATISTICALLY SIGNIFICANT CORRELATIONS OF THE IBI MEAN PER TRIAL FEATURE OF THE ECG MODALITY

	IBI Mean per trial	
Q3 (Drowsiness)	0.258**	Sig=0,001
Q5 (Concentration)	-0.176 **	Sig=0,001

A statistically significant negative correlation was also identified between the boredom question (Q3), and the frequency-domain feature of the LF to HF ratio. In particular, the LF to HF ratio mean value during each trial demonstrated a correlation coefficient value of τ=-0.205 (p<0.001) regarding Q3. This was also an expected result, since in our experiment the state of drowsiness is connected with a decrease in mental workload, correlated in the literature with an increase in the HR LF/HF Ratio.

Furthermore, we investigated the normalized IBI mean per trial feature's overall alteration between the Gameplay and Graphics trials. In order to do so, we calculated the feature's average value for all the subjects' Gameplay and Graphics trials respectively. For the Gameplay trials, this feature had the average value of 0.269, whereas for the trials using the graphics game version, this average was 0.447. Since the Heart Rate is calculated as the inverse of the Inter-Beat Intervals, we conclude that subjects had in average an increased heart rate during the Gameplay trials, than during the graphics ones. Taking into account that increased heart rate is strongly related in the literature with higher levels of arousal, this result is a strong indication that during the Gameplay trials, subjects felt more aroused. This arousal could either mean enjoyment, tension or frustration but nevertheless shows a higher level of involvement and immersion into the game world.

B. GSR

As shown in table 4, the level of EDA during the first 20s seemed to correlate positively with Flow (the negative correlation in Table 4 is due to the fact that the score of Q4 was inversely proportional to the Flow) and positively with concentration questionnaire. This indicates that both concentration and flow increase EDA, which is an expected result, as flow is thought to be a combination of high arousal and pleasure.

TABLE 4
EDA CORRELATIONS: CORRELATION BETWEEN EDA(FIRST 20S OF THE TRIAL) AND QUESTIONNAIRE DATA FOR FLOW AND CONCENTRATION

	EDA First 20s
Q4 (Flow)	-0.241** Sig=0,000
Q5 (Concentration)	0.235** Sig=0,000

The average value of the normalized "GSR mean per trial" feature for all the Gameplay trials was found to be 0.295, whereas the corresponding one for all the graphics trials was 0.395. Furthermore, for the vast majority of the subjects the average of the normalized GSR mean for the Gameplay trial was much higher than the one for the trial with the graphics version. By taking into account the fact that higher average EDA levels are strongly connected to higher levels of arousal and pleasure, this result came to further support our conclusion regarding the subjects' higher levels of arousal during playing the challenging version of the labyrinth, as was indicated also from the corresponding game experience questionnaires and ECG modality analysis described above.

C. EEG

Some of the features extracted from the EEG modality slightly correlated with the subjects self assessment of boredom before the eye blinks were removed. However, an extra feature was included in this analysis, namely a rough estimate of the number of eye blinks. This number displayed the same correlation as the above mentioned features. This could be expected as eye blinks severely contaminate the power estimates in the theta and alpha regions [24]. This could mean the correlations found in the EEG features were due to eye blink artifacts. This is confirmed in the section about eye blink removal, where we show that the power in the theta and alpha regions is strongly reduced after removal of the eye blinks. After the removal of the eye blinks none of the correlations seemed to be significant anymore, which again confirms the fact that the eye blinks are responsible for the correlation. For future work, we could consider the number (and maybe the length) of the eye blinks as a measure for attention.

We also tried the sample entropy [25] for quantifying the regularity of the signal as regularity seems to change depending on the mental state (drowsiness or attention) of the subject. This is by no means confirmed in literature and is just an extra possibility we wanted to check. This feature, too, did not seem to correlate with the information in the questionnaire.

D. EMG

After analyzing the correlations between the extracted EMG features and the answers to the questionnaires, we found out that our most representative of the overall muscle activity feature, "EMG_AvgRatiosA", was positively correlated to the questions identifying the subject's drowsiness / boredom and frustration. In particular, a significant correlation was found between this feature and the boredom (Q3) question (τ=0.122, p=0.008) as well as the frustration (Q2) question (τ=0.293, p<0.001).

This result can be considered as an indication that through trials, as the subjects get tired, bored and frustrated of the repetitive task, their overall behavior changes, and this is reflected within the change of the agonist/antagonist ratios extracted as features from the rectified averaged EMG signals. In particular, by taking into account the fact that higher values of this feature in our case usually appeared in mouse movements of higher range of motion and velocity, one may conclude that the specific correlation found is an indicator of the subject's tendency for mouse movements of higher velocity and range of motion while getting more frustrated during the experimental session.

VIII. CONCLUSIONS

In this work we aimed to combine outcomes obtained from various research fields such as presence, affective computing and psychology in order to evaluate video gaming experience and identify psychophysiological correlates of changes in the user's affective state during HCI. For this purpose, within the eNTERFACE 09 project 1, two VR-biosignals experiments were conducted. The first experiment compared gameplay features and challenges with "purely" technical game parameters like graphics and sound, whereas the second focused on the identification of psychophysiological and behavioral correlates of the changes in the user's affective state during repetitive tasks in HCI. During the workshop, data was collected from 21 subjects who played different versions of the VR game repeatedly, while their EEG, EMG, ECG and GSR signals were recorded.

Regarding the graphics vs gameplay debate, both subjective and objective assessments conducted for the purposes of Experiment 1, showed an increase in involvement and immersion for the game version with the game challenges. These results are strongly supported by the analysis of

biosignals features related to pleasure and arousal (mean GSR activity level and mean IBI) which showed that during playing the challenging version of the labyrinth game, subjects were in average more excited than during playing the version with graphics of high quality and no challenges. This excitement showed to correlate to different causes between subjects with significant gaming background and the ones without. In particular, experienced players clearly enjoyed the gameplay version more than the others, as indicated by the questionnaire scores, while players not familiar with games found the challenges difficult for them and therefore did not seem to prefer any particular version. This is an important outcome that can be used in the analysis of gaming experience and specifically the affect of the gameplay design in players with different gaming experience.

During Experiment 2, by having a large number of repetitions of the same labyrinth game as stimuli, we managed to elicit the affective state of drowsiness / boredom to all subjects participated. After appropriate analysis (based on the Kendall's tau correlation coefficient) of the data collected we managed to identify statistically significant correlations between features extracted from the monitoring modalities and the changes in the subjects' affective state during the experimental session. The most significant correlations identified at the p=0.001 level were related until now to the ECG, GSR and EMG modalities.

Conclusively, the main outcomes of the project's experiments were the development of a rich biosignals database related to gaming experience, of techniques regarding the pre-processing of the raw data collected, the identification of more objective measures regarding the gaming experience, and the extraction and statistical analysis of features from biosignals. The focus was towards the development of classification methods regarding the changes of the user's affective state during HCI. One task of high importance for the development of automatic biosignals-based classifiers, able to distinguish effectively the transitions in the human affective states during VR games and HCI in general, is the selection of appropriate features derived from the monitored biosignals. Towards this direction, this work has examined such features, in an attempt to identify significant ones that could be used in the future for the automatic classification of the affective states of a VR game player.

ACKNOWLEDGEMENTS:

We would like to thank all eNTERFACE participants that participated as subjects for the purposes of the Project 1 experiments.

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APPENDIX A

QUESTIONNAIRES

eNTERFACE Project1 experiment questionnaire

Pre-questionnaire

Participant ID:

Briefing

In this experiment we try to identify psychophysiological correlates of the human affective states during Human – Computer Interaction. For the purpose of the experiment, you will play a "Labyrinth" VR game repeatedly, while your biosignals will be monitored from EEG, ECG, GSR and EMG sensors. You are free to withdraw from the experiment at any time.

Questions asked before starting placing the sensors

Do you have any known to you medical problem that would not allow you to participate in the experiment?

Yes No

Right - Left Handed

I consent to take part in the experiment

Personal Information

Name:
Age:
Sex:
Height:
Weight:
Do you use biofeedback in your work? Yes No

Game Experience

1. How often do you play video games? (hours / week)

2. How often do you play 3D maze or first-person shooter games? (hours/week)

3. How many years of game experience do you have?

4. What type of games do you usually play?

- ☐ First / Third - Person Shooter
- ☐ Strategy Games
- ☐ Role Playing Games (e.g. WoW)
- ☐ Adventure (e.g., Monkey Island, King's Quest…)
- ☐ Action (e.g. Prince of Persia)
- ☐ Sports / Racing Games
- ☐ Casual Games (e.g. Tetris, Chess, Music games etc.)
- ☐ Educational Games / Serious Games

Train Data acquisition session questionnaire

Video 1

1. How much attention did you pay on the video?
   Not at all 1 2 3 4 5 Very much
2. The video was
   Unpleasant 1 2 3 4 5 Pleasant

Video 2

1. How much attention did you pay on the video?
   Not at all 1 2 3 4 5 Very much
2. The video was
   Unpleasant 1 2 3 4 5 Pleasant

3. How do you feel?

- calmed 1 2 3 4 5 agitated
- interested 1 2 3 4 5 bored
- happy 1 2 3 4 5 sad
- 1 2 3 4 5 frustrated

Mid-trials questionnaire

Trial 1

Do you want to play the game again?

No, I'd rather do something else 1 2 3 4 5 Yes

How do you feel?

Frustrated Not at all 1 2 3 4 5 Very much

Bored of the game Not at all 1 2 3 4 5 Very much

How aware were you of events occurring in the real world around you and of your personal thoughts?

Not at all 1 2 3 4 5 Very much

How concentrated were you on the game?

Not at all 1 2 3 4 5 Very much

Trial 1 game experience questionnaire (Game Version 1)*

	not at all	slightly	moderately	fairly	extremely
I felt successful					
I felt bored					
I found it impressive					
I forgot everything around me					
I felt frustrated					
I found it tiresome					
I felt irritable					
I felt skilful					
I felt completely absorbed					
I felt content					
I felt challenged					
I felt stimulated					
I felt good					

Trial 2

Do you want to play the game again?

No, I'd rather do something else 1 2 3 4 5 Yes

How do you feel?

Frustrated Not at all 1 2 3 4 5 Very much

Bored of the game Not at all 1 2 3 4 5 Very much

How aware were you of events occurring in the real world around you and of your personal thoughts?

Not at all 1 2 3 4 5 Very much

How concentrated were you on the game?

Not at all 1 2 3 4 5 Very much

Trial 2 game experience questionnaire (Game Version 2)*

	not at all	slightly	moderately	fairly	extremely
I felt successful					
I felt bored					
I found it impressive					
I forgot everything around me					
I felt frustrated					
I found it tiresome					

I felt irritable					
I felt skilful					
I felt completely absorbed					
I felt content					
I felt challenged					
I felt stimulated					
I felt good					

Trial 3-10+

Do you want to play the game again?

No, I rather do something else 1 2 3 4 5 Yes

How do you feel?

Frustrated Not at all 1 2 3 4 5 Very much

Bored of the game Not at all 1 2 3 4 5 Very much

How aware were you of events occurring in the real world around you and of your personal thoughts?

Not at all 1 2 3 4 5 Very much

How concentrated were you on the game?

Not at all 1 2 3 4 5 Very much

Post-questionnaire**

1. How much did the visual aspects of the environment involve you?
   Not at all 1 2 3 4 5 Very much
2. How aware were you of events occurring in the real world around you?
   Not at all 1 2 3 4 5 Very much
3. How well could you concentrate on the assigned task?
   Not at all 1 2 3 4 5 Very much
4. Did the sensors disturb you while trying to complete the game?
   Not at all 1 2 3 4 5 Very much
5. Were you involved in the experimental task to the extent that you lost track of time?
   No 1 2 3 4 5 Yes

* Based on [38]

** Based on [39] and [40]

A sensor pairing and fusion system for a multi-user environment

Jari Kleimola, Maurizio Mancini, Giovanna Varni, Antonio Camurri, Carlo Andreotti, Longfei Zhao

***Abstract*—This paper proposes a system for sensor pairing and fusion in an interactive multi-user environment. Using the system, we integrated mobile accelerometer and fixed position optical tracking methods, and implemented two active music listening applications based on the movement interaction from one or more users. We found that an acceleration domain similarity index between the two tracking methods is able to pair the raw interaction streams in near real-time, and that concurrent sampling of the streams allows for easy sensor fusion. Although these algorithms still require further refinement, we believe that combining accurate position with accurate acceleration data is beneficial for novel interactive applications.**

***Index Terms*—interactive multisensor systems, mobile phones, music, sound synthesis, tracking**

I. Introduction

In the recent past, when mobile phones were used primarily for voice and SMS communication, phone microphone and keypad sufficed to fill the interaction needs of most users. Today, a growing number of phones embed accelerometers, cameras, compass, GPS, and touch sensors, which extend the number of available input modalities, context processing capabilities, and use scopes well beyond the original communication scenarios. Mobile phones are becoming fundamental players in user-centric media applications: they can be used as multimodal interfaces, or personal transducers having many uses for our everyday lives.

However, these extended input capabilities are rarely utilized in contemporary interactive applications. To date, interactive applications are mostly exploiting fixed external sensors (for example, fixed cameras for motion or color tracking) that provide "traditional" kind of input streams, such as exact coordinate positions in a well defined coordinate system.

Most embedded mobile sensors are not well suited for producing this type of traditional input. For example, a phone camera can be used to compute approximate coordinate positions using optical flow, but the resulting data is often too inaccurate. Likewise, an integrated accelerometer can provide high resolution acceleration data that is precise, but when double-integrated to obtain the coordinate positions, the cumulative errors in the processing phase result in inexact data.

This work aims at providing methods to support the creation of usable, effective mobile applications, resting on the balance between traditional techniques based on environmental sensors (e.g., fixed video cameras) and embedded mobile sensors. That is, methods implementing sensor *pairing* and *fusion*. For example, traditional camera-based tracking fails to detect minimum acceleration deviation while gesturing: precise coordinate position, but poor acceleration data can be obtained, due to noise in double derivation. On the other hand, accelerometers provide precise acceleration data but poor coordinate position due to noise in double integration.

The work we are presenting in this paper is based on the assumption that we are acquiring synchronized data from different sensors from multiple users. Performing *sensor pairing* corresponds to identify to which user each data refers to. *Sensor fusion* occurs when we are able to use the paired combined data from different sensors referring to every single user.

More precisely, this eNTERFACE project addresses the following research problems that are currently investigated by the SAME project :

- How to combine mobile and fixed position camera – based data tracking with phone embedded accelerometer tracking, in order to integrate and exploit the best properties of both approaches;
- To study whether it is possible to extract high level motion features by exploiting this integration;
- To analyse and compare the pros and cons of the two data acquisition methods.

For these aims, we propose a system for sensor pairing and fusion in a multi-user environment. In particular, we implemented two active music listening scenarios: the Audiovisual Air Instruments and the Mobile Conductor.

In the direction of defining novel active listening paradigms , Camurri et al. recently developed a system, named Orchestra Explorer, allowing users to physically navigate inside a virtual orchestra, to actively explore the music piece the orchestra is playing, to modify and mold in real-time the music performance through expressive full-body movement and gesture. By walking and moving on the surface, the user discovers each single instrument and can operate through her expressive gestures on the music piece the instrument is playing. The interaction paradigm developed in the Orchestra Explorer is strongly based on the concept of navigation in a physical space where the orchestra instruments are placed. The Orchestra Explorer

Manuscript received November 19, 2009. This work was supported in part by the European Union (EU) as part of the 7th Framework Programme with the SAME project (ref. 215749).

Jari Kleimola is with the Dept. of Signal Processing and Acoustics, Helsinki University of Technology (TKK), Espoo, Finland (jari.kleimola@tkk.fi).

Maurizio Mancini, Giovanna Varni and Antonio Camurri are with the Infomus Lab, Dept. of Communication, Computer and System Sciences (DIST), University of Genova, Italy (maurizio.mancini@dist.unige.it, Giovanna.varni@gmail.com, antonio.camurri@unige.it).

Carlo Andreotti and Longfei Zhao are with the Dept. of Communication, Computer and System Sciences (DIST), University of Genova, Italy.

paradigm has been implemented in two different scenarios. The first is based on users tracking by fixed video cameras observing the sensitive space where user(s) can navigate and interact with the sections of the virtual orchestra. A second version is based on mobile systems (Nokia S60 family of mobiles), where the onboard 3D accelerometer is used to navigate a colored cursor on a map representing the orchestra in the phone display.

Camurri et al. propose also a more sophisticated active listening paradigm , where multiple users can physically navigate a polyphonic music piece, actively exploring it; further, they can intervene on the music performance modifying and molding its expressive content in real-time through non verbal full-body movement and expressive gesture. An implementation of this system, named Mappe per Affetti Erranti, was presented in the framework of the science exhibition "Metamorfosi del Senso", held at Casa Paganini, Genova, in October – November 2007. In that occasion Mappe per Affetti Erranti was also used for a contemporary dance performance.

The reminder of this paper is organized as follows. Section II provides a system overview, while sections III through V explain the system in detail. Sections VI and VII present the implemented application scenarios. Finally, Section VIII discusses the outcomes and perspectives of this project.

II. SAME project framework for Active Music Listening

Our system is developed in the SAME networked platform, which is an end-to-end framework (i.e., between clients of a mobile service, producers and consumers of the content) for context-aware, experience-centric mobile music applications, enabling embodiment and control of music content by user behaviour. The platform includes one or more remote or local servers, running software environments such as EyesWeb XMI , Pd and vvvv .

Remote SAME servers may provide services related to the access and retrieval of audiovisual content (e.g., music content, see fig. 1), as well as the remote support of users. Local SAME servers may include services connected to the physical environment, as in our case, the real-time processing of the signal from a fixed position camera. The services include also the ability to process and manage the applications based on the interactions captured from the mobile phones.

The mobile phones may embed MobIO environment, which is a multimodal mobile IO framework developed in the SAME project.

A. System description

In this work, we propose a system for sensor pairing and fusion using the components of the SAME project framework. The hardware setup consists of mobile phones (e.g., Nokia N85 and N95), which are connected to a PC via a wireless network. The PC interfaces also a fixed position video camera, a projector, a MIDI synthesizer and a loudspeaker setup.

The PC runs a local SAME server, hosting three applications (see fig. 2). *EyesWeb* is responsible for video tracking, gesture recognition, feature extraction and MIDI playback. *Pd* is used as a sound synthesizer, while *vvvv* serves as the graphics engine.

Figure 1: SAME platform in a streaming configuration. The mobile phone can send and receive data with two servers: the CORE server handles the phone requests, while the Streaming server deals with the content streaming.

The mobile phones run an embedded application utilizing the *MobIO* framework. The application is responsible for capturing the accelerometer and mobile camera streams from the phone embedded sensors, and routing them to the local SAME server applications for further processing and audiovisual synthesis tasks.

The components are connected together using IP-based Open Sound Control (OSC) and EyesWeb proprietary streaming video protocols.

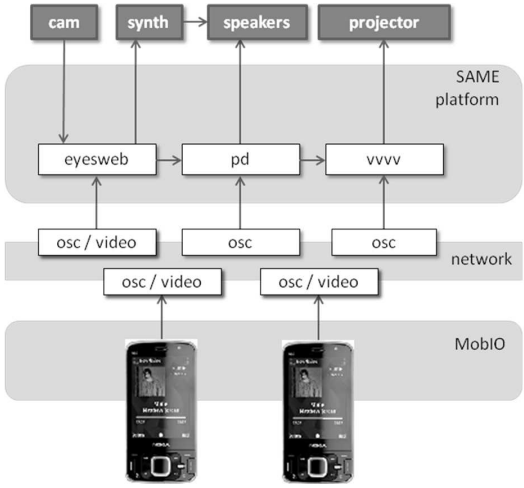

Figure 2: SAME project framework in a local configuration.

Figure 3 depicts the conceptual diagram of the system. Low level features are captured from the mobile phones, either by using the sensors of the phone itself, or by using a fixed camera tracking the position of the phone. The high level features (impulsivity, curvature and so on) are computed from these data. The audiovisual output of the system is then computed by

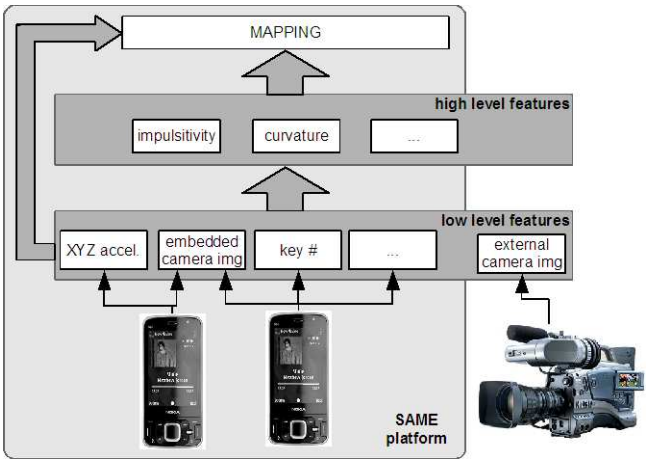

Figure 3: A system for sensor pairing and fusion in a multi-tracking environment.

the result of a mapping process.

III. LOW AND HIGH LEVEL FEATURES

This section describes the low level data acquisition and high level formulation tasks utilizing MobIO and EyesWeb environments.

A. Inputs from the mobile phones

The accelerometer and camera sensors of Symbian-based mobile phones, such as Nokia S60 devices, are accessible through C++ APIs that – unfortunately – depend on the operating system version of the phone. The MobIO framework models these sensors as black boxes, attempting to hide the version differences between the different APIs. The boxes are also equipped with input and output ports in order to have a consistent parametrization interface across different classes of objects, and more importantly, affording the construction of dataflow networks from the interconnected boxes. This concept is semantically equivalent to the graphical programming paradigm employed in EyesWeb, Pd and vvvv environments, but because MobIO has programming language bindings, the syntax level is different.

MobIO calls these black boxes *Units* that can be interconnected to form *Patches*. In this work, the patch encapsulates dataflow paths for streaming the accelerometer data as OSC messages (Acc → OSCWriter → UDPOut), streaming the video to the EyesWeb (Cam → EyWImageStreamOut), processing the video and streaming the optical flow out as OSC (Cam → MeLib → OSCWriter → UDPOut), and detecting and generating keypress events (Key → OSCWriter → UDPOut). The Acc, Cam, Key and UDPOut units encapsulate the raw input and output APIs of the Symbian SDK. The OSCWriter unit generates OSC-formatted messages within /acc, /key and /opt namespaces. The EyWImageStreamOut unit converts the raw video stream of the phone camera into a 64x64 pixel grayscale bitmap stream before forwarding it to the EyesWeb. Finally, MeLib unit interfaces a phone hosted motion estimation library , capable of producing a stream of positional changes in the horizontal, vertical, distance and rotational dimensions.

B. Inputs from the fixed and mobile camera

The video signal provided by a fixed camera is processed in real-time by an EyesWeb application (or *patch*). It identifies blobs corresponding to the mobile phones. Each mobile phone screen shows a different color, see Figure 4. A color-based tracking allows us to follow the 2D position of the phones frame by frame in the video stream. The tracking module takes as input a list of the blobs detected in the current frame of the video stream and compares them with the blob list detected in the previous frame and stored in an internal buffer of the module. A weighted distance area criterion is used to match and track blobs frame by frame.

The mobile camera sends video stream to an EyesWeb patch that performs the optical flow computation on this stream. The flow is computed on each video frame compared to the previous ones. For each pixel of the frame we obtain the movement vector (dx,dy) that represents how much and in which direction the pixel has moved between the two frames. Then we compute the frame mean optical flow on the X and Y axis separately as the arithmetical mean of the X and Y components of each pixel movement vector.

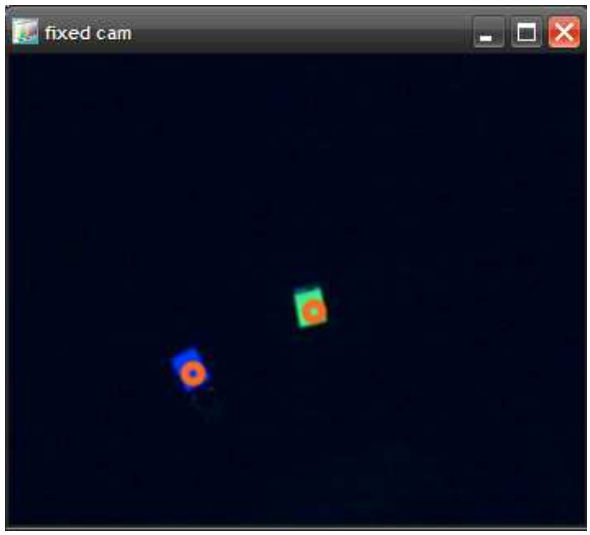

Figure 4. EyesWeb tracking the mobile phones.

C. Expressive Motion Features

The algorithms for the automatic evaluation of motion features, have been implemented in the EyesWeb software platform (www.eyesweb.org) using the EyesWeb Expressive Gesture Library . From the low-level features described above, we computed the following motion features:

- *Impulsivity* (computed from mean optical flow) indicates whether or not movement presents sudden and abrupt changes in energy. We define impulsive gestures as those characterized by short duration and high magnitude.
- *Directness* (computed from absolute acceleration) is a measure of how direct or flexible a trajectory between two

points in space is. We obtain it by comparing the length of the minimal distance between the two points with the length of the actual gesture trajectory.

• *Velocity* (computed from absolute acceleration) corresponds to the first order derivative of the gesture trajectory coordinates.

IV. Sensor pairing and synchronization

This section describes two alternative algorithms for sensor pairing and synchronization.

A. Real-time Pairing and Synchronization

The pairing of the acceleration measured from the mobile phone and the acceleration from the computer–vision based tracker engine was developed by means of a real-time EyesWeb XMI application.

Two users are in front of the fixed camera and they frontally move, respectively, (i) a mobile phone showing a green marker and (ii) a red marker. The user with the mobile performs a shaking movement, whereas the other user freely moves the marker. The absolute acceleration is computed both from the accelerometer and from the second order derivatives of the barycenter coordinates of the colored markers tracked by EyesWeb. Then, a *similarity index* among these absolute accelerations is extracted providing a criterion to pair the accelerometer with the corresponding colored blob.

, There are 3 streams coming from the acquisition: (i) acceleration from the mobile accelerometer; (ii) acceleration from the green marker tracking (also related to the mobile movements); (iii) acceleration from the red marker tracking. A generalized auto-correlation function is computed for each stream and then it is normalized to zero mean and unitary standard deviation. Finally, the application performs a correlation coefficient (the Correlation Probability of Recurrence) among the generalized auto-correlation function of the mobile acceleration and the generalized auto-correlation functions of the tracked markers acceleration and a numeric comparison is done. The marker having the highest correlation coefficient is associated to the accelerometer in the mobile phone.

B. Offline Pairing and Synchronization

Regarding to the limitations of hardware and software, significant noise is present, which is not easy to cancel or at least reduce to an acceptable level (in terms of system usability). For example, because of the pre-emptive nature of the operating system, the 3D accelerometers embedded in mobile phones have time-varying sampling that produce non-uniform latency. Likewise, without an embedded orientation sensor it is impossible to determine the angle between the phone and the fixed position camera. In some conditions, these errors lead to unexpected pairing results, and therefore the analysis is split into pre-processing and matching parts.

The *pre-processing* part aims to remove useless information from the original data, to smooth and to find out the potential information, to let them available for subsequent evaluation algorithms. Because we perform the analysis in the acceleration domain, the position extracted from the fixed camera tracking is double-differentiated in this part. Also, considering the orientation of mobile phone is undetermined when moving, we introduce Energy Space by using quadratic sum of accelerations to ignore the orientation.

In the *matching* part, three algorithms (Wing, Covariance and Row) are used to check the similarity between the two acceleration data sets. Custom coefficients are given to these algorithms according to different hardware setups. If one set of data from accelerometers meets the highest total score with another set of data from the camera, they're determined to be a pair.

- The *Wing algorithm* is an extension of peak detection, it evaluates the similarity using the shapes of signals. A wide and high wave denotes a strong action. The probability for the other one to follow should then be larger. So the Wing Algorithm is related with the sum of such probabilities on each wave.

- The *Covariance algorithm* returns the correlation coefficients calculated from an input matrix [*x*, *y*], where *x* is the acceleration from accelerometer Energy Space, and *y* is the acceleration from camera in Energy Space.

$$r_{xy} = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{(n-1)s_x s_y} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\,\sqrt{n\sum y_i^2 - (\sum y_i)^2}}.$$

- The *Row algorithm:* Rate based on Observe Window Algorithm evaluates the strength similarity of the signals based on magnitude ratio in observe window of Energy Space. Observe Window can remove small fluctuation, which makes the rate comparing method more robust.

The pairing method turned out to be reliable and robust when the 2D movement was strictly perpendicular to the camera. To extend to more general 3D movement, the orientation of the mobile phone itself is needed. And for dedicate hardware, parameters determined based on some tests will lead to a better synchronization performance.

V. Communication among system modules

The system modules are interconnected using IP-based protocols (see fig. 2). In particular, the input and output namespaces of the two implemented active music listening scenarios are described using OSC address strings and their numerical arguments. On the input side, the interaction data consists of three-axis acceleration (/acc ax ay az), two-dimensional position (/pos x y) and key press (/key code state) events. The arguments of the /acc messages are normalized to floating point g-forces ranging from -2g to 2g. The position is expressed as a floating point coordinate pair in a (0,1) times (0,1) plane, roughly covering the reachable area in front of the user. The key presses from the mobile phone keypad are con-

verted to ASCII, with a Boolean state indicating down or up position of the key.

The interaction streams from the two mobile phones are transmitted separately, and prefixed by a mnemonic name tagged to the mobile. For example, the accelerometer stream of the first phone is transmitted as "/blue/acc x y z", while the position of the second would be given as "/green/pos x y". The tags can either be fixed at the phone end, or created dynamically according to the pairing procedure described in Section IV A.

The mobile video stream is transmitted as an EyesWeb proprietary streaming protocol. The payload of the stream consists of uncompressed grayscale images.

VI. Scenario 1: Audiovisual Air Instruments

In this scenario, the user plays a virtual musical instrument by gesturing in the air. The instrument is controlled either by impulsive vertical hand gestures (strokes), or more relaxed horizontal actions (sweeps), and it responds by producing synchronized aural and visual feedback.

In the installation, the user stands in front of a large projection screen and a loudspeaker setup, holding two mobile phones in his hands. The mobile phones are used as input transducers, or virtual drum sticks / mallets, generating raw interaction streams. The system analyzes the input streams in order to extract the stroking and sweeping gestures, tracks the positions of the phones, and renders the interaction using aural and visual rendering engines.

The aural output is generated by a software sound synthesizer, producing pitched and non-pitched percussive FM timbres in response to vertical strokes, and low-pitched scanned synthesis timbres in response to the sweeping gestures. The audio synthesizer is polyphonic (i.e., capable of generating multiple notes simultaneously), and multi-timbral (capable of synthesizing multiple sounds at once).

The visual output engine is also capable of rendering multiple objects and visual timbres simultaneously (see fig. 5). The strokes are visualized as animated circles that are enlarged and faded away in synchrony with the percussive sound. The scanned synthesis instrument is visualized as a slowly rotating 3D pearl of interconnected plates. The plates are animated also in the vertical dimension according to the force imposed by the interaction gesture.

A. Mapping

Table 1 summarizes the mapping procedure of the Audiovisual Air Instruments scenario. Raw accelerometer (/acc), position (/pos) and key press (/key) input streams are routed to a processing component that translates the input events into the language of the rendering engines. The processing involves gesture extraction from the /acc and /key streams, sensor fusion of the /pos coordinates and /acc energy, and finally, sending the detected and parametrized gesture events (/stroke x y E or /sweep x y E) to the rendering engine for final mapping into the native rendering speak (/note pitch velocity).

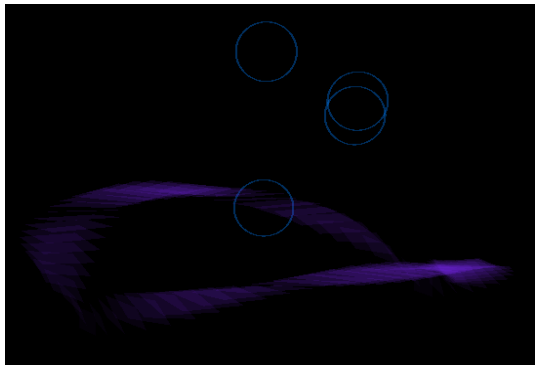

Figure 5. Graphical output of the Audiovisual Air Instruments scenario.

In addition, the state of the physical model of the scanned audio synthesis engine is transmitted periodically to the graphics engine as an array of 128 samples (/wavetable T).

Table 1. Multistage mapping in the audiovisual air instruments scenario.

raw input	gesture	fusion	rendering
/acc ax ay az	/stroke	energy E	/note pitch vel
/key code s	/sweep	-	
/pos x y	-	x y	
			/wavetable T

B. Processing

A Pd patch receives raw /acc, /key and /pos streams as sequential OSC packets arriving at a single UDP port. The patch first separates the streams of the two mobiles (/blue and /green) into identical parallel chains of execution. Processing continues thereafter according to the next token of the OSC address string.

For /acc packets, the patch first calculates the energy of the movement ($E = \mathrm{sqrt}(ax^2 + ay^2 + (az-1)^2)$), and generates a new stroke event when the calculated value exceeds a threshold of 1.57. The algorithm enters then into a wait state, and does not generate new events until a 100 ms time delay has expired. The triggered stroke event is extended with position information by sampling the current value of the /pos stream. The x and y positions of the phone and the calculated energy value E are transmitted to the rendering engines as '/stroke x y E' messages.

The accelerometer data is also used in forming horizontal sweeping gestures. This gesture is triggered by pressing and holding the middle navigator button of the mobile phone. While pressed, the position stream is sampled constantly at 10 Hz rate. The accelerometer energy is calculated at the same rate, resulting in a new '/sweep x y E' message that is transmitted to the scanned synthesis engine at each sampling instant.

C. Rendering the audio and graphics

The '/stroke x y E' messages are converted into '/note pitch velocity' messages (with a fixed one second duration) and routed internally inside the Pd to a *dssi~* external hosting a

hexter plugin . Hexter is a DSSI plugin emulating Yamaha's DX7 FM synthesizers, and it is capable of rendering original DX7 patch files and operating in multi-timbral and polyphonic playing modes. Experimental versions of the dssi~ and hexter modules were ported to the Windows platform as part of this work. In the final mapping stage, the x, y and E arguments of the message are transformed either into the pitch or velocity parameter of the '/note pitch velocity' message. For example, after informal user evaluation we noticed that a marimba timbre worked best when x was mapped to the pitch and E to the velocity. We experimented also by quantizing the x-range into four zones, each triggering a different sound from the synthesizer (y was then mapped to the pitch and E once again to the velocity).

The stroke messages are also transmitted to a vvvv patch, which extracts the x and y arguments of the message, and renders a circular Rope primitive at the central position denoted by the extracted arguments. The scaling and the alpha channel values of the rendered item are animated using an ADSR node.

The '/sweep x y E' messages are routed inside Pd to a custom scansynth~ external developed in this work. The external implements a scanned synthesis oscillator with an internal physical model consisting of 64 mass-spring-damper elements chained into a form of a circular string. The synthesized sound is produced by scanning a slowly changing wavetable at audio rates. The wavetable update rate is parametrized, and is typically around 20 Hz. During the update, the vertical positions of the masses are sampled into the amplitude values of the wavetable, which is then played back at a low pitch in order to produce a wide background sound layer for the more percussive FM timbres generated by stroking. The x argument of the message selects a single mass from the circular string, the y argument is bound to the vertical displacement parameter of the mass, and the E argument to the initial velocity of the mass. Thus, by sweeping, the user is able to induce disturbances to the physical model, thereby exciting it to produce sound.

The sweep message is not transmitted to the graphics engine. Instead, each update of the wavetable transmits the entire newly scanned wavetable to a vvvv patch, which updates its internal graphical model accordingly. The model consists of simple semitransparent Quads arranged into a circular 3D spread of length 64. Each wavetable sample value is mapped to the Y-translation parameter of the Quad. In order to make the model more organic, displaced Quads are also rotated around y-axis using a Damper node. The entire structure is also rotated slowly around y-axis by using a LFO node.

The FM and scanned synthesis modules are able to generate sound simultaneously. The 2D circles and the 3D string model are also coexistent in the graphics engine, and layered on top of each other.

VII. Scenario 2: Mobile Conductor

The Mobile Conductor scenario enables active experience of music: the user can express herself in conducting virtual musicians playing a prerecord MIDI piece of music. The mobile phone is here used to detect the movement of the user hand and to mold the execution style by modulating the music speed, volume and intonation.

Figure 6: an illustration of the Mobile Conductor paradigm.

The user holds the phone in her hand. By performing quick or slow gestures she determines the music playback rate (e.g., quick gesture stands for quick playback and vice versa). Linear and straight hand trajectories raise the performance volume, whereas spread and curved trajectories lower it. The user can further process and manipulate the audio content: for example, if the user shakes the mobile phone by performing sudden stroke gestures, then the execution intonation of the active musical instrument is modified by an impulsive perturbation (e.g. a temporary pitch detune). Thus, the user can conduct and manipulate with assigned degrees of freedom the virtual musicians by experimenting all the three above features at the same time.

The music rendering is either based on loudspeakers or directly on the mobile phone using its headphones. In the latter case, the music is sent to the network and is received on the mobile phone where the user can listen to it by headphones.

A. Mapping

The Mobile Conductor scenario uses both the three-axis acceleration data, sent via OSC messages, and the image captured by the mobile camera sent through UDP protocol. The mapping is organized in two steps: (i) from low to high level motion expressive features; (ii) from high level features to MIDI messages.

First steps consists in the following:

- *from absolute acceleration to a measure of "impulsivity"*: we compute the squared sum of the three acceleration components along the X, Y and Z axis; in this way we can filter out the gravity component by simply subtracting 1 to the resulting acceleration. Impulsivity of movement is defined as a ratio between the movement acceleration amplitude over its duration, see Section IV for more details.
- *from movement coordinates to the measure of "directness"*: 2D movement coordinates are computed from the optical flow on the image stream sent by the mobile camera. Starting from 0.5 to 4 seconds buffers

of coordinates in the X,Y plane we build movement trajectory, using temporal segmentation algorithms, then we evaluate how such trajectory is spread with respect to a straight line connecting the first to the last position in the trajectory.

The second step provides the MIDI messages to be sent to the audio output module:

- *"impulsivity" mapping to MIDI pitch change*: when impulsive movements are detected, the system produces a sequence of pitch change MIDI messages, in the range of +/- 25 around the regular pitch of the music piece. The result is that if the user shakes strongly the mobile phone the output audio becomes out of tune for a while, consistently with the sudden, impulsive "shake" of the device.
- *"directness" mapping to MIDI volume change:* as the trajectory performed by the user with her mobile phone approximates a straight line, that is, the "directness" feature is high, we send MIDI messages that increase the volume of the music piece and vice-versa.
- *"speed of movement" mapping to MIDI speed change*: the speed of movement comes from the derivation of movement coordinates; this is mapped on MIDI messages that modify the music piece playback rate. The higher speed of movement, the higher playback rate, and vice-versa.

B. Outputs to the user: Midi audio

The Mobile Conductor scenario produces a MIDI output of a music piece. MIDI allows us to easily modulate the speed, volume and intonation of the execution in real-time.

For this purpose, we implemented two EyesWeb blocks: Midi File Reader and Midi Message Generator (see fig. 7).

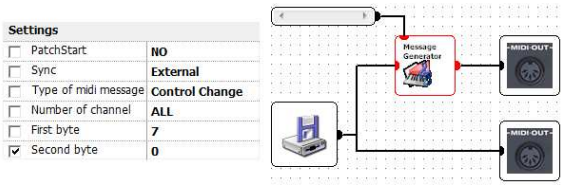

Figure 7: EyesWeb patch to control playback volume . The settings table shows that a "Control Change" message has to be generated for "ALL" channels. The message's second byte carries the volume value and it can be changed in run-time with the slider at the top left of the patch.

The *Midi File Reader* has the following output modes:

- Multi-channel output: all the messages of a channel are sent trough out that channel's dedicated output line.
- Mixed-channel output: all the midi messages read from the input file are sent trough out the output line without taking care of the message's channel.
- Buffered output: the output is buffered and sent out after the buffer becomes full. The size of the buffer can be set manually, or calculated automatically from the external audio clock signal.

Moreover, there are three synchronization modes:

- Internal clock: the execution period is calculated from the values read from the input midi file such as the "Time division" value located in the file header chunk and the various Tempo values carried by the "Set Tempo" meta-event messages.
- External audio clock: a new input pin is created which can be connected to an external audio clock signal (such as an audio buffer signal). The timing properties of the midi track (such as Tempo and Tick length) are read from the midi input file like in the previous synchronization mode, but this time the output mode is automatically switched to "Buffered output" and the length of the midi buffer is calculated to match the values acquired from the external audio signal. In this way, each time an audio buffer is generated from i.e. an mp3 reader block, a midi buffer with the same length is generated too. This is very useful to synchronize a midi file with an external media source.
- User specified: the "Time division" and "Set tempo" meta events are ignored, and the execution period is set manually.

The *Midi Message Generator* allows to manually generate some midi messages. The user must specify the type of the message, he can choose between: Note Off, Note On, Polyphonic key pressure, Control Change, Program Change, Channel pressure, Pitch Bend and Real Time Message. Then he can specify the values of the two byte message's payload. The block checks the midi channel number and, if the value is between 1 and 16 it creates the message for the specified channel and sends it out like in the original behavior; if the midi channel number instead is set to "ALL" the block creates and sends trough the output pin sixteen midi messages, one for each midi channel. This block can be used i.e. to modify the volume or the "pitch bend" of every midi channel at the same time.

VIII. Discussion

In this work we developed a system for sensor pairing and fusion in the specific case of interactive mobile applications. We presented two implementations on active music listening, based on movement interaction from one or more users, integrating onboard accelerometers and external video cameras. We investigated low level motion descriptors, and utilized these in the formulation of higher level, expressive motion features and gestures. We then designed the mapping of movement on music, sound synthesis and animation.

The low level input streams are captured from mobile phone embedded accelerometers and cameras, and from a fixed position camera tracking the color of the mobile phone screens. The fixed camera with blob tracking provides 2D position information, the mobile camera with optical flow techniques is used to compute the velocity, while mobile accelerometer provides the acceleration data.

Targeting multi-user environments, we were interested in finding ways to do sensor pairing, i.e., to identify which two separate anonymously tracked streams originate from a particular device. We found that by calculating a similarity index between two acceleration streams (as obtained from the mobile

accelerometers and from a double differentiated blob tracking stream), it is possible to pair the streams of the two tracking mechanisms. On the other hand, targeting interactive applications, we were also interested in doing sensor fusion, i.e., synchronizing and combining the paired streams into a more descriptive interaction stream. Here we found that an event based push protocol, such as OSC, allows for easy implementation. Unfortunately, we cannot conclude anything about the limits of the acceptable synchronization latency, because it depends on the output parameter mapping.

We were also interested in finding whether it is possible to extract high level motion features from the mobile phone accelerometer streams, and whether it is possible to do optical flow natively inside the mobile phone. We were able to derive impulsivity of motion successfully, although the slow sampling rate of the accelerometers (37 Hz) - coupled with the buffering delay of the impact gesture recognition - made the system feel unresponsive in the test applications, in particular when triggering new notes. The optical flow from the mobile phone was even slower (15 fps) than the accelerometer stream. The same 15 fps applied also to the raw video stream captured from the mobile camera.

The implemented application scenarios revealed that the mapping process is sequentially distributed between the system components. We found that it is most convenient to normalize the parameter ranges as early in the sequence as possible (for example, transforming the accelerometer readouts into |2g| range inside the mobile phone itself, instead of transmitting sensor-specific values). This could be addressed for example by utilizing the MobIO abstraction mechanisms. Considering the output stage, the scanned synthesis algorithm, possibly with remote wavetable implementation, seems to be an attractive mobile audio synthesis method.

In conclusion, it is possible to pair the fixed camera-based blob tracking streams with the accelerometer-based mobile tracking, but that is not a trivial task. However, although the slow sampling rates of the mobile phone sensors pose some limits to the applicability, combining the exact position with the exact acceleration data proved to be clearly beneficial, and therefore we plan to further refine the similarity index algorithm.

Contribution and Acknowledgment

The contributions of the authors are as follows. Jari Kleimola (project coordination, MobIO framework, audiovisual air instruments), Maurizio Mancini (project co-coordination, mobile conductor), Giovanna Varni (Sensor pairing in EyesWeb, mobile conductor), Antonio Camurri (project revision), Carlo Andreotti (EyesWeb MIDI blocks implementation), and Longfei Zhao (offline Matlab analysis of sensor pairing).

The authors would like to thank Barbara Mazzarino for mobile conductor application feature extraction, Corrado Canepa for EyesWeb application design, and Gualtiero Volpe and Paolo Coletta for project revision.

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Toward a model of computational attention based on expressive behavior: applications to cultural heritage scenarios

D. Glowinski[1], M. Mancas[2], P. Brunet[3], F. Cavallero[1], C. Machy[4], P.J. Maes[5], S. Passchalidou[6], M.K. Rajagopal[7], S. Schibeci[1], L. Vincze[8], G. Volpe[1]

[1] University of Genoa, Italy, [2] University of Mons, Belgium, [3] Queen's University of Belfast, UK, [4] Multitel, Belgium, [5] University of Ghent, Belgium, [6] University of Crete, Greece, [7] Telecom Paris, France, [8] University of Pisa

Abstract

Our project goals consisted in the development of attention-based analysis of human expressive behavior and the implementation of real-time algorithm in EyesWeb XMI in order to improve naturalness of human-computer interaction and context-based monitoring of human behavior. To this aim, perceptual-model that mimic human attentional processes was developed for expressivity analysis and modeled by entropy. Museum scenarios were selected as an ecological test-bed to elaborate three experiments that focus on visitor profiling and visitors flow regulation.

***Index Terms*—museum, computational attention, expressive behavior, complexity.**

I. HUMAN BEHAVIOR ANALYSIS IN MUSEUM SCENARIOS

The analysis of the behavior exhibited by museum visitors is interesting from different perspectives. In museography, the design of an exhibit or of a visit to an archeological site could greatly benefit from concrete data from the automated tracking and analysis of visitors' behavior, to obtain a profiling of the museographic project. From the perspective of the enhancement of the quality and the intensity of the experience in a museum visit, many directions can be envisaged: from the analysis of the behavior of visitors used to adapt the lighting environments, the communicated museum multimedia content, to the increase of the immersivity and the understanding of cultural content by means of interactive technologies, toward an "active fruition" of cultural content [11]. Furthermore, these issues can provide inspiration toward, for example, possible solutions to the well-known problems of the "Non-Places" which are defined by Marc Augé as places where no social relationship can take place [2].

Multiple variables affect the museum experience: 1) the artifacts that are exhibited, 2) the visitor's personality, knowledge, motivation or learning style, 3) the presence and dynamics of others around them including friends, family and strangers, and 4) the environmental conditions (e.g., signage, light, temperature). In this sense, museum experience has been described as a *multivariate* one [38]. Other aspects of our daily lives spent in public spaces also show great complexity and sensitivity to multiple social, cultural and psychological influences (e.g., go shopping). However, Bell's *cultural ecologies* ascribe museum visit with three specific qualities: *liminality* (museum are places that embody an experience apart from everyday life, in a differently experienced dimensions of time and space), *engagement* (museums are places where people go to learn, often in an entertaining and exploratory way) and *sociality* (museum should be designed to guide supported activities that increase the interaction between family members, friends and artifacts) [4].

Museums are receiving in the recent years an increasing interest from the Information and Communication Technologies ICT research communities. On one hand, non-invasive systems for monitoring people and user modeling (e.g., ubiquitous computing, ambient intelligence) can enable visitor profiling with reliable quantitative data, which can give new insights on visiting styles. On the other hand, the development of interactive applications can provide visitors with new solutions for active fruition of museum content.

II. SUPPORTIVE ICT FOR MUSEUMS FRUITION SCENARIOS

A. *Profiling visitors*

Starting from observations of the behavior of visitors in several museums, the ethnologists Veron and Levasseur [34] argued that visitor behavior can be classified as four "animal-styles": *ant*, *fish*, *butterfly* and *grasshopper*. The *ant* visitor follows a linear path and spends a lot of time observing almost all the exhibits. The *fish* visitor moves mainly in the centre of the room without looking at exhibit's details. The *butterfly* visitor often changes visiting direction and stops frequently. Finally, the *grasshopper* visitor carefully selects a number of exhibits and spends a lot of time observing them while ignoring the others (see Figure 1). This classification have been widely used and supported by quantitative analysis [35, 31, 18, 15, 43]. An alternative simplified museum visitor typology was proposed by Sparacino following Dean [17] that distinguish between three types of visitors: the *busy*, *selective*, and *greedy* visitor type [31]. The *busy* type wants to get an overview of the principal items in the exhibit and see little of everything, the *selective* type wants to see and know in depth only about a few preferred items and the *greedy* type wants to know and see as much as possible without time constraint.

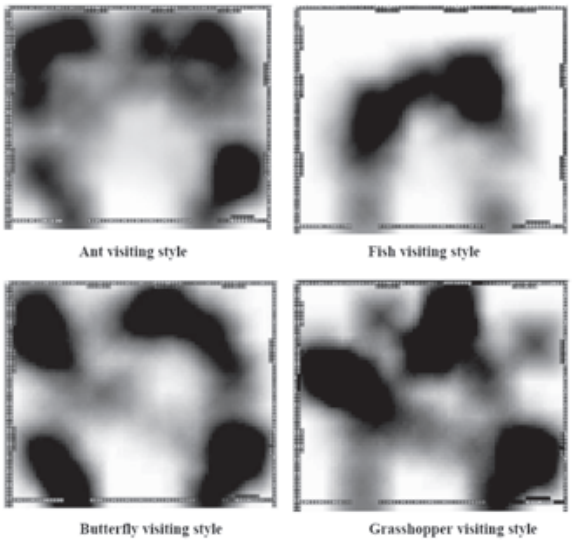

Fig. 1*: Overview of the four visiting styles developed by Veron and Levasseur* [34] *and modeled with the VU-FLOW system developed by Chittaro et al.* [15]*. The darker areas represent spaces where a visitor spent a lot of time.*

Both visit typologies are based on spatial-temporal patterns that characterize visitor displacements in the museum (e.g., physical path, speed, direction changes, number, location and length of stops). In addition, these patterns of displacement can be employed to identify navigation problems within the museum spaces [15, 30]. Unobtrusive monitoring systems (e.g., ambient intelligence technologies) allows for the automatic capture of physical data related to visitors' behaviors [29]. However, in a number of real-world scenarios, the identification of individuals for the purpose of tracking can be problematic (e.g., occlusion, video coverage of the exhibit) and can require additional manual annotation [30]. More invasive devices (wearable museum [31], virtual environment [15]) have been employed to provide more accurate and robust information about position and orientation, however with the possible drawback of restricting or influencing visitor behavior.

B. Providing visitors with active fruition of museum content

The information automatically collected from movement patterns enable curators to profile visitors and identify design exhibits problems offline. Ambient intelligence and user modeling technologies have also been largely used to extend the possibility of interaction within the museum spaces. A majority of projects have developed context-sensitive handheld prototypes with embedded sensors which are employed to capture visitor current location, in addition to handle more explicit request from visitors.

The Hippie project is a first attempt to develop a context-sensitive adaptive museum guide [28]. Their user model aims to "predict the information needs of a user in a given episode of a visit". The model makes inferences regarding the next exhibit to visit and the next piece of information to present. In the HIPS [26] and the museum wearable project [31], visitor styles, based on the patterns from [34] and [31], serve to assemble appropriate length audio clips for each individual (e.g..for the *butterfly* or *greedy* type, short clips will be displayed).

Experimental mobile multimedia systems have also been developed in the MUSE and PEACH projects to personalize information [16, 32]. The PEACH guide provides the visitor with a digital character on their PDA who delivers information on various artifacts within the exhibits. Details about paintings can be accessed through prerecorded video close-ups and a printout can be produced to recapitulate the exhibits the visitor encountered while at the museum. The MUSE project provides virtual access to physically unavailable items according to a visitor's interest.

The e(ch)o project implements hybrid adaptive and adaptable systems to correlate explicit and implicit reactions from users to gain feedback and improve user model [18]. The CHIP project allows a user to generate a personal profile via an online rating system for artwork that is later used by the system to suggest visit itineraries in the museum [1].

In recent years, research has continued on group-based activities. In this perspective, the PDA is thought to provide shared virtual space for coordination and collaboration to help make new connections for museum visitors [4]. The PIL Project, for example, extends results of the PEACH project from the individual to the group level [19, 21]. The authors developed intra-group context-aware communication services that aim at stimulating conversation about the museum contents within the group, during and after the visit. Wakkary observed that the interest for group-based activities vary from research focused on information delivery tours to research focus on game interaction activities [40, 39]. A learning game for school children has been created within the ARCHIE project [33]. It allows visitors to trade museum-specific information to gain points in order to win a game. However, during group-based activities, handheld device like a PDA may distract the visitors from their companion. In this perspective, recent ambient intelligence techniques based on group-centric concepts [36] can reveal fruitful for non-invasive applications in museum environments (Shape project [3], Kurio project [41]). InfoMus – Casa Paganini in particular developed novel user- and group- centric interactive multimedia system architecture enabling an active and social experience of audiovisual content in a playful manner. The first permanent interactive museum exhibitions focused on music performance and full-body movements as first class conveyors of expressive and emotional content. For the Music Atelier of "Città dei Bambini" (Children's City, Genova, 1997), a *sensitive* space was designed to let children exploring music content through expressive body movements. In the Genovese Maritime museum and the aquarium, systems were implemented for the real-time control and generation of sounds and musical comments related to the content of the museum exhibit ("The Big Blue Boat",2000). Interactive sonification depended on individual presence in specific locations and group movements. Scientific museum served as a testbed for active exploration of scientific experiments to trigger interest and curiosity and to facilitate the commitment of young visitors ("Museo del Balì", Fano, 2004, "Museo Vivo della Scienza - Fondazione IDIS", Napoli). From the perspective of valorization of cultural heritage, recent research conducted in InfoMus Lab - Casa Paganini have provided

novel engaging paradigms of interaction with pre-recorded music content, enabling a large number of non-expert users to rediscover the musical heritage (e.g., classical and contemporary music) they may not be familiar with (EU-ICT Project SAME, Sound and Music for Everyone, Everyday, Everywhere, Every Way, www.sameproject.eu). The field of application has been extended to active experience of audiovisual content, in particular in a novel permanent interactive museum exhibition: Palazzi in Mostra, Palazzo Ducale, Genova, Italy, enabling tourists and visitors to explore virtually the UNESCO Treasure of "Palazzi dei Rolli" in Genova (2010).

III. OUR PROPOSAL

A. Analysis of non-verbal expressive gesture

1) From explicit to implicit tagging

Regarding the user characteristics that need to be modeled, most approaches focus on physical data (movement patterns) to reconstruct visiting style. Higher-level of information related to social or affective interactions can also be retrieved from the analysis of visitors' non-verbal behavior. Vinciarelli labels this process "implicit tagging" [37] in contrast to explicit tagging paradigm in which a data item gets tagged only if a user actually decides to associate tags with it (e.g., adding keywords to the data that are used for indexing and retrieval purposes). Discrete emotions of visitors (e.g. anger) or attitudinal states (e.g. boredom) can be communicated through full-body or body-part movements such as the hands and head. As mentioned by Nass and Brave, emotions are displayed in a similar way in human-human and in human-computer interactions [8]. These categories of gesture that convey an affective message are called expressive gestures [, camurri2005cea].

According to Kurtenbach and Hulteen, a gesture can be defined as "a movement of the body that contains information" [22]. Thus, gestures can be named expressive since the information they carry includes content related to the emotional sphere. Expressive gesture, as a key aspect of human behavior and in particular of expressive human behavior, became particularly relevant in recent years (e.g., see the post-proceedings of Gesture Workshops 2003, 2005, and 2007). Psychological studies have been a rich source for research on automatic analysis of expressive gesture since they identified which features are most significant [27, 42, 7]. A further relevant source has been research in the humanistic tradition, in particular choreography. As a major example, in his Theory of Effort, choreographer Rudolf Laban [23] describes the most significant qualities of movement. Starting from these sources, several systems for analysis of expressive gesture were developed [10, 20, 5]. Our approach starts from the multilayered framework for automatic expressive gesture analysis proposed by Camurri et al. [12]. In this framework, expressive gestures are described with a set of motion features that specify how the expressive content is encoded. The EyesWeb XMI platform for synchronized analysis of multimodal datastreams (www.eyesweb.org) allows for the extraction of a wide collection of motion features from video and sensors data streams.

2) From static to dynamic modeling

Recently, we developed a novel technique to make analysis of expressive gesture context-sensitive and adaptive. Our approach draws upon information theory and computational attention and has resulted in a salient index that detects salient (i.e. unusual) behaviors. Behavior saliency accounts for the distance, in a selected time window, between the expressive features measured on an individual and the averaged values measured on all the components of the group. Saliency can be computed with respect to time or to space depending on the behavioral features that are considered (e.g., dynamics for time, trajectory for space).

Behavior saliency can be modeled starting from recent results obtained in the field of *computational attention*. The aim of computational attention is to automatically predict human attention based on different kinds of data such as sounds, images, video sequences, smell, or taste. In this framework, salient behavior is understood as a behavior capturing the attention of the observer. Whereas many models were provided for attention on still images, time-evolving two-dimensional signals such as videos have been much less investigated. Nevertheless, some of the authors providing static attention approaches generalized their models to the time dimension (for a detailed review, see [24]). Motion has a predominant role and the temporal contrast of its features is mainly used to highlight important movements. Boiman and Irani [6] provided an outstanding model which is able to compare the current movements with others from the video history or video database. Attention is related to motion similarity. The major problem of this approach is in its high computational cost. In order to get an efficient model of motion attention and behavior salience, we developed a three-level saliency-based model [24]. At the first level, motion features are compared in the spatial context of the current video frame; at the intermediate level, salient behavior is analyzed on a short temporal context; at the third level, computation of saliency is extended to longer time windows. An attention/saliency index is computed at each of the three levels based on an information theory approach. Analysis of salient behavior was recently extended to measures of complexity namely *Multi-scale Entropy* (MSE). This method aims at evaluating the complexity of finite length time series. It is based on the analysis of the entropy values assigned to the original time series and to coarse-grained time series, each of which represents the system's dynamics on a different scale.

B. Pilot experiments

At the occasion of the Enterface09 summer school, three pilot experiments were carried on to address issues related to visitor profiling and visitor-flow regulation.

1) Visitor profiling

A first setup was created to implement and test a real-time dynamic modeling of Veron and Levasseur visiting styles [34] based on the long-term saliency index. Five Arcimboldo's painting reproductions were displayed in a gallery style on the stage of the Casa Paganini auditorium. The typical spatial configuration theorized by Levasseur and modeled in many recent studies (see *section II. A*) was followed: three paintings

on the length side and one on each of the width sides of the stage (see Figure 2).

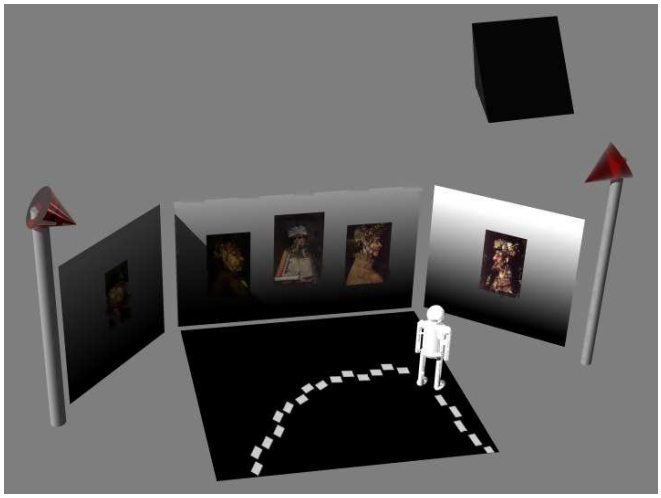

Figure 2. *The gallery style setup : illustration of a visitor in the five paintings museum room*

Participants were instructed to view the images as they typically would in a museum. Each participant was asked to visit the gallery set up three time: (i) alone, (ii) in presence of two confederates that view paintings from empty spaces (*empty* condition) and (iii) in presence of two confederates that view paintings by standing directly in front of them (*full* condition). These single user and multi-user scenarios were created respectively to (i) observe and model visiting styles and (ii) to put in evidence how the presence of others influence visiting style. Five paintings from the Arcimboldo opera pre-rated to be similar in attractiveness were selected for the gallery. We thus avoid that visual characteristics of a particular painting could differentially capture the visitor's attention.

Participants' movements were observed from a single infra-red video cam positioned 12 meters above. Motion history images (MHI) were used to compute the position, the direction and the velocity of participants over long-time scales (e.g., 4 minutes). The saliency index computed from these features allowed to build a model of the scene highlighting the regions where salient behaviors, characterizing visiting styles, could be observed [25]. The unusual direction changes that characterize the *butterfly* style or the long periods of observating select paintings typical of the *grasshopper,* for example, could all bedetected. Four learnt models were successfully built that respectively integrate the characteristics of each Levasseur animal-styles. Tests on 10 male participants revealed that the main styles of the visitor could be dynamically modeled in single and multi-users scenarios. Results revealed that most participants followed the ant-like style when alone and a grasshopper-like style in presence of others. Contrary to other static classifications [26, 31, 43], our model could inform in real-time on how the current visit deviate from a pre-determined pattern [see Figure 3]. Less typical behaviors could actually be retrieved that combine more animal-like styles. Further tests will be needed that could lead to more detailed typologies of visiting styles.

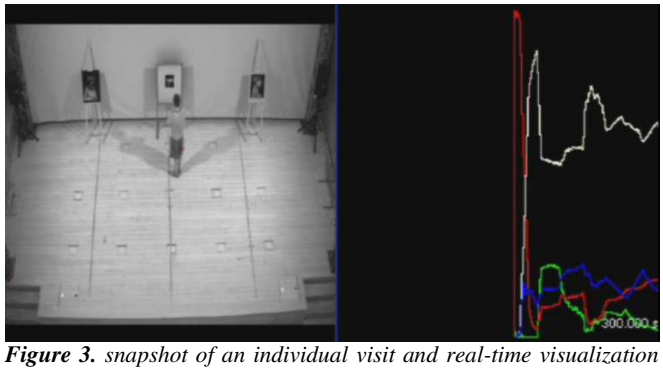

Figure 3. *snapshot of an individual visit and real-time visualization of each visiting style value (ant-green, grasshopper-blue, butterfly-red, fish-white)*

Personality questionnaires were also administered to the participants to investigate any possible correlations between visiting styles and behaviors observed in the various scenarios with personality traits. Participants completed the short form version of the Big Five Inventory (BFI) and the 5-highest loaded shyness items and the 5-highest loaded sociability items [9] from the Cheek and Buss Shyness and Sociability Scale [13, 14]. Results suggest that participant's visiting style can be differentially affected by the presence of others according to his sociability score. Two classes of people were highlighted: those who change their style when other visitors are present (on the path they would normally take) and those who do not. In the full condition, we found that the five participants that deviated from the ant pattern scored statistically significantly lower on the sociability scale than the five participants that maintained their ant pattern [$F(1,7) = 8.556$, $p = .022$)]. In our sample, people who feel the least comfortable with others tend to drastically change their visiting style to avoid standing too close other people.

2) Regulating visitor-flow

The second and third experiments were setup to explore interactive applications that could regulate visitors flow in a museum. The experiments again took place on the Casa Paganini stage with the same video setup for tracking participants' displacements.

The second experiment aimed, in particular, at finding visual cues that would guide a visitor to a target position. In our test-case, the size and the resolution of the visual display (an image of an Italian historical Palace) were mapped with the distance of the visitor's current position from the target position (see figure 4). When the participant approached the target position, the image projected on the 8*4 meters screen that stood back along the stage, appeared in its full resolution and size. When the participants moved away, the image decreased and blurred.

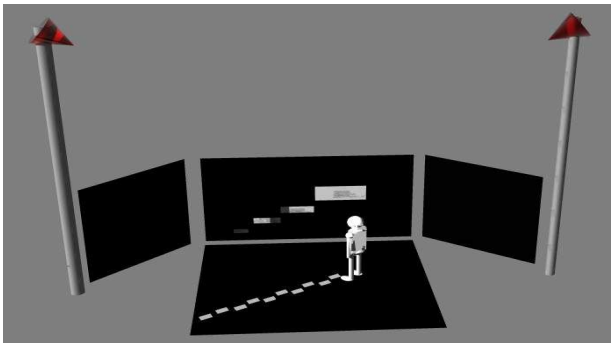

Figure 4*. The visitor located in the target position is able to watch the projection in full size and full resolution (no blur effect).*

Various mapping combination were explored (e.g., trials including only blur effect without size changes of the images, trials including only participant displacement along horizontal axis). As illustrated in Figure 5, tests on 14 participants revealed that the target position was reached more directly and rapidly (less than one minute) when the size and resolution of the image were both mapped to the participant displacement on the horizontal and depth axes of the stage. A set of expressive features was developed to analyze participants' space occupation during the experiment and evaluate the interaction design thoroughly.

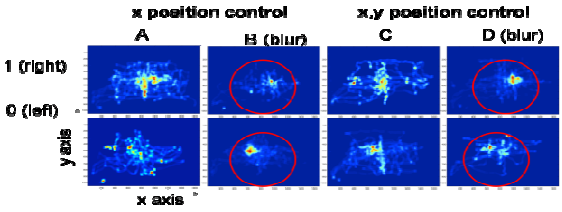

Figure 5*. Expressive features related to space occupation. Example of the max Density features, visualization of 14 users mean positions over time.*

Psychological profiles were also submitted to the participants. People who performed low on the sociability scale (i.e. introvert people) reported greater interest in the size/resolution manipulations ($r = -.606$, $p = .022$).

The third experiment aimed at regulating visitor-flow in a museum room by guiding each individual to available artworks. The gallery style setup described in the first experiment was reproduced. A long-term motion attention model of the scene was developed to compute how the region surrounding each painting was visited as compared to the others. Salient regions were then sorted out according to their density level. Visitor-flow was regulated by attracting a new visitor's attention by means of a projected arrow to the most salient regions, i.e, the region surrounding artwork that was currently not being viewed by anyone else (see Figure 6).

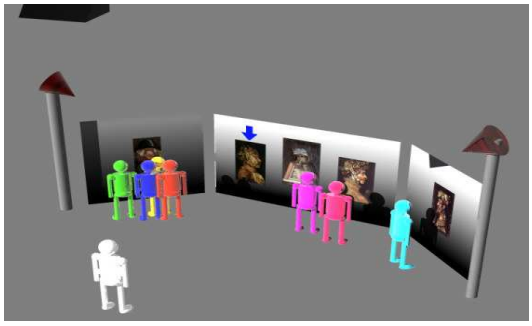

Figure 6*. A view of the interaction: new visitors entering in the room were encouraged to watch the less visited paintings*

IV. *Conclusion and Future Work*

The work presented was achieved during the one-month enterface09 summer school, and it should be considered as a starting point for future analysis work, currently in progress. In particular, we investigated the potential applications of computational attention models to museum scenarios. Three pilot experiments were conducted to address issues related to visitor profiling and visitors flow regulation. Preliminary results revealed that the standard Veron and Levasseur four visiting styles could be modeled dynamically using a real-time long-term attention model. Visitors expressive behavior in the museum-like exhibit was further considered by analyzing space occupation during the experiments and exploring possible correlations with personality traits. Basing on previous results, an interactive application aimed at supporting natural expressive behavior was designed and tested to regulate visitor-flow. A last consideration is on the first successful use of the Casa Paganini site as a test-bed for developing active fruition paradigm for museum applications.

Acknowledgments

This work has been achieved in the framework of the eNTERFACE 2009 Workshop at the Casa Paganini – InfoMus Lab of the University of Genova (Italy). It was also included in the Numédiart excellence center (www.numediart.org) project 3.1 funded by the Walloon Region, Belgium. Finally, this work has been partially supported by the Walloon Region with projects BIRADAR, ECLIPSE, and DREAMS, and by EU-IST Project SAME (Sound And Music for Everyone Everyday Everywhere Every way). We also thank Prof. Bracco, Chiorri, Schenone for their precious advice.

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Donald Glowinski.

Donald Glowinski, Paris, 27-02-1977. His background covers scientific and humanistic academic studies as well as high-level musical training.- EHESS (Ecole des Hautes Etudes en Sciences Sociales) MSc, in Cognitive Science, CNSMDP (Conservatoire National Supérieur de Musique et de Danse de Paris) MSc in Music and Acoustics, Sorbonne-Paris IV MSc. in Philosophy. He recently obtained a Phd in computing engineering at InfoMus Lab – Casa Paganini, in Genoa, Italy. (dir: Prof. Antonio Camurri).
He was chairman of the Club NIME 2008 (New Interfaces for Musical Expression), Genoa, 2008. His research interests include multimodal and affective human-machine interactions. He works in particular on the modeling of automatic gesture-based recognition of emotions.

Matei Mancas.

Matei Mancas was born in Bucarest in 1978. He holds an ESIGETEL (Ecole Supérieure d'Ingénieurs en informatique et TELecommunications, France) Audiovisual Systems and Networks engineering degree, and a Orsay University (France) MSc. degree in Information Processing. He also holds a PhD in applied sciences from the FPMs (Engineering Faculty of Mons, Belgium) on computational attention since 2007.

His past research interest is in signal and, in particular, image processing. After a study on nonstationary shock signals in industrial tests at MBDA (EADS group), he worked on medical image segmentation. He is now a Senior Researcher within the Information Processing research center of the Engineering Faculty of Mons, Belgium. His major research field concerns computational attention and its applications.

Paul M. Brunet

Paul M. Brunet was born on February 12, 1980 in Sudbury, Canada. In September, 2009, he obtained a PhD in Developmental Psychology from McMaster University in Hamilton, Canada. Previously, he held a one-year fixed-term Assistant Professor position at Mount Saint Vincent University in Halifax, Canada. Currently, he is a Research Fellow under the direction of Prof. Roddy Cowie at Queen's University Belfast in Belfast, Northern Ireland. Paul is also a member of the Social Signal Processing Network.

His research interests include the effects of context and individual differences on social communicative behavior, the social signals of politeness, the influence of individual differences in personality (in particular shyness and sociability) in typical development, and cyberpsychology.

Pieter-Jan Maes

Pieter-Jan Maes was born on May 16, 1983 in Kortrijk, Belgium. He is currently working on a PhD project supervised by Prof. Dr. Marc Leman, director of the Department of Musicology (IPEM) at Ghent University.

His research interests are grounded in the embodied music cognition paradigm and cover the relationship between movement, sound and musical meaning. Based on results of experimental research, he develops music HCI-applications for the music education, performance and gaming sector.

Francesca Cavallero.

Francesca Cavallero, Genova, 27-12-1982. Coming from humanistic academic studies (she holds the Master's degree in Arts and Multimedia at University of Genova, DAMS - Discipline delle Arti, della Musica e dello Spettacolo, with a thesis on evaluation issues on new paradigm of embodied active listening: a specific case study has been developed on the evaluation of the behavior of subjects using an interactive installation), she is PhD student in Arts and New Technologies (DIRAS - Liberal-Arts Faculty, University of Genova).
From 2006 she collaborates with Casa Paganini InfoMus Lab (dir: Proff. Antonio Camurri). Her research interests concern the user behavior in museographic contexts, to develop new models of active fruition for cultural assets.

Stefania Schibeci

Stefania Schibeci, Sanremo, 02-04-1982. Her training is in humanistic academic studies; she holds the Master's degree in Arts and Multimedia at University of Genova, DAMS - Discipline delle Arti, della Musica e dello Spettacolo, with a thesis about the importance of the body concept in the art of XX s (in particular in the Pina Bausch Tanztheater, in Pippo Delbono's and Societas Raffaello Sanzio's theatre and in the body art).

Laura Vincze.

Laura Vincze was born on April 8th, 1982 in Cluj-Napoca, Romania. She is a PhD student in Linguistics, University of Pisa. Her research interests include multimodal communication, persuasion (non verbal and verbal strategies) in political discourse. She recently concluded a research period at the Faculty of Humanities, University of Amsterdam where she focused on the pragma-dialectical approach to argumentation.

In 2008 Laura held a seminar at the University of RomaTre on analysis of non verbal signals of agreement/disagreement and dominance/submission in political debates.

Manoj .K. Rajagopal

Manoj kumar Rajagopal was born on February 9 , 1982 in Mettur Dam , India. He is currently working on PhD project supervised by Dr.Patrick Horain ,Telecom ,Sudparis ,France and Dr.Catherine Pelachaud , Telecom Paristech , France.

His research interest are Machine Learning , Communicative gestures and Human Computer interaction. Presently he is working on style parameters for the human communicative gestures also to develop an avatar for the gestures communication of different style using GRETA.

Stella Paschalidou

Stella Paschalidou was born in Thessaloniki in 1977. She holds a BSc in Physics (Aristotle Univ. Thessaloniki) and an MSc in Music Technology (Univ. of York). She has been working since 2004 as a teaching assistant at the TEI of Crete, dept. of Music Technology&Acoustics and has worked in the Telecommunications private sector in the past.

Her main interests include multimodal interactive systems for musical applications and real-time analysis of expressive content, especially in orally transmitted music traditions

Gualtiero Volpe.

Gualtiero Volpe, Genova, 24-03-1974, PhD, computer engineer. He is assistant professor at University of Genova. His research interests include intelligent and affective human-machine interaction, modeling and real-time analysis and synthesis of expressive content in music and dance, multimodal interactive systems.

He was Chairman of V Intl Gesture Workshop and Guest Editor of a special issue of Journal of New Music Research on “Expressive Gesture in Performing Arts and New Media” in 2005. He was co-chair of NIME 2008 (New Interfaces for Musical Expression), Genova, 2008. Dr. Volpe is member of the Board of Directors of AIMI (Italian Association for Musical Informatics).