The Dancer in the Eye: Towards a Multi-Layered Computational Framework of Qualities in Movement

Antonio Camurri
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
antonio.camurri@unige.it

Gualtiero Volpe
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
gualtiero.volpe@unige.it

Stefano Piana
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
stefano.piana@dist.unige.it

Maurizio Mancini
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
maurizio.mancini@unige.it

Radoslaw Niewiadomski
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
radoslaw.niewiadomski@dibris.unige.it

Nicola Ferrari
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
eusebius_1799@yahoo.com

Corrado Canepa
Casa Paganini – InfoMus
DIBRIS, University of Genova
Genova, Italy
corrado@infomus.org

ABSTRACT
This paper presents a conceptual framework for the analysis of expressive qualities of movement. Our perspective is to model an observer of a dance performance. The conceptual framework is made of four layers, ranging from the physical signals that sensors capture to the qualities that movement communicate (e.g., in terms of emotions). The framework aims to provide a conceptual background the development of computational systems can build upon, with a particular reference to systems analyzing a vocabulary of expressive movement qualities, and translating them to other sensory channels, such as the auditory modality. Such systems enable their users to "listen to a choreography" or to "feel a ballet", in a new kind of cross-modal mediated experience.

Author Keywords
Cross-modal and multimodal interactive systems; Dance performance; Expressive movement; Automated analysis of movement qualities; Interactive sonification.

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INTRODUCTION
In his uncanny cosmic mysticism, ancient Persian poet Rûmi claimed that the action of closing eyes is needed for really seeing, because it makes us search for that light that is more evident and clear than the manifest and visible one.

This idea is at the basis of the conceptual framework we propose in this paper, i.e., a framework to guide the design and the development of systems for automated analysis of expressive movement qualities. The rationale is that if we can capture the inner and intimate qualities (e.g., in terms of emotions) movement conveys to an external observer, these qualities can be made manifest and visible through other sensory modalities such as, for example, the auditory one. In such a way, by closing her eyes and by listening to the auditory representation of movement qualities, a user can be made aware of some information, which is hidden in the movement and may be difficult to perceive otherwise.

The proposed framework consists of four layers, ranging from physical signals to high-level qualities of movement (and dance) performance and addresses several aspects such as different spatial and temporal scales. It was developed within the EU-H2020 ICT Project *DANCE*[1], which aims at investigating how sound and music can express, represent, and analyze the affective and relational qualities of body movement. To transfer vision into sound, however, a model

[1] http://dance.dibris.unige.it

is needed to understand what we see when we observe the qualities of a movement, and what we perceive in a movement when we feel its qualitative expression. The model presented here, while focusing on the visual analysis of movement qualities, is propaedeutic to their multi- and cross-sensorial translation.

The paper is organized as follows. The next section reviews some related work; our framework is then described layer-by-layer; finally, on-going and future work, with particular focus on existing or planned implementations is discussed.

RELATED WORK

Developing computational models of full-body expressive movement in nonverbal communication is a challenging interdisciplinary research problem. It involves dance and choreography (e.g., Rudolph Laban's Effort Theory [16]), experimental psychology (e.g., [29]), affective computing (see some recent surveys on analysis of nonverbal affective content in full-body movement [17][18]), neuroscience (see e.g., the study by de Gelder on the role of the body in conveying emotion [10]). Camurri and colleagues [4][5][7] proposed a multi-layered model of expressive gesture, which was adopted in the EyesWeb libraries for expressive gesture analysis (e.g., [9][14]). Recent studies focused on computational models inspired by artistic research, see for example the work by Alaoui and collegues to analyze the vocabulary of choreographer Emio Greco [1]. Moreover, analysis of expressive full-body movement qualities proved useful in research on ICT for therapy and rehabilitation of cognitive and motoric disabilities including, e.g., Parkinson disease [8], autism [22], and chronic pain [26].

With respect to our previous work in [4][5][7], the proposed framework (i) is more explicitly connected to an observer's perspective, (ii) takes into account different spatial and temporal scales, (iii) establishes a clear distinction on the types of data in each layer and introduces specific analysis primitives, and (iv) explicitly targets expressive qualities.

CONCEPTUAL FRAMEWORK

The framework we propose here develops from the multi-layered framework for analysis of nonverbal expressive content in full-body movement defined in [4][5][7]. Our proposal grounds on the following basic assumptions:

1. *Observer Perspective*: we assume the perspective of an observer of a dance performance, rather than the (egocentric) perspective of the dancer. For example, an observer may perceive the movement of a dancer as *light*, but the movement can actually be the result of strong muscular forces and tensions the dancer exerts in order to convey *lightness* to an audience.
2. *Body-Space Scales*: we assume that a specific subset of expressive movement features can be measured at different Body-Space Scales, ranging from a single part of the body (e.g., a hand), to the whole body, up to a group of dancers perceived as a single body/organism. For example, *contraction/expansion* can be measured on the movement of one hand, of the whole body, or of a group of dancers; *coordination* can be measured both in terms of intra-personal synchronization (either of joints of a limb or of the whole body), and of inter-personal synchronization of dancers within a group. Body-Space Scales are related to the distinction between *Personal Space* and *General Space* proposed in R. Laban's Effort Theory [16], and adopted in the design of the expressive libraries of the EyesWeb system [5].
3. *Temporal Scales* (from continuous to discrete time): we assume that different time scales apply to different kinds of analyses and extracted features. Low-level features are usually measured as instantaneous qualities; mid-level features typically require time windows in a range of 0.5-3s [11][24]; high-level features, concerning e.g., emotion and social signals, are measured at larger time scales. As long as the analysis moves from low-level signals to high-level concepts, the focus of the analysis moves from continuous time-series of sampled data to events happening at discrete locations in time.
4. *Multimodality*: our model is conceived to fully exploit multimodal integration of motion capture, visual, audio, and physiological data. Respiration features contribute, for example, to analysis of expressive movement.
5. *Analysis Primitives*: we assume that analysis primitives are applied to data at various stages in the model. Analysis primitives are unary, binary, or *n*-ary operators that summarize with one or more values the temporal development of a feature in an analysis time unit (e.g., a movement unit or a time window). Statistical moments (for example, average, standard deviation, skewness, and kurtosis) are among the simplest unary analysis primitives. Further examples of unary operators, that are

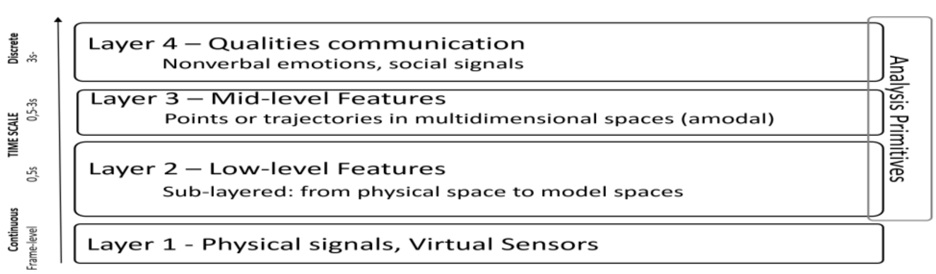

Figure 1. Conceptual framework.

more complex, include shape (e.g., slope, peaks, valleys [9]), entropy [13], recurrence [27], and time-frequency transforms. Analysis primitives also include predictive models (e.g., HMMs as in [2]), or physical models, such as the mass-damper-spring model adopted in [23].

Figure 1 sketches the overall structure of our multi-layered conceptual framework. In the next subsections, we describe each layer in more detail.

Layer 1 – Physical signals: Virtual sensors

Layer 1 (*Physical signals*) grounds on the concept of *virtual sensor*, understood as a single physical sensor (or as the integration or fusion of data from many physical sensors) combined with signal conditioning (e.g., denoising and filtering), and with techniques for extraction of specific raw data. For example, an RGB-D physical sensor (e.g., Kinect) may be associated with virtual sensors providing the 3D trajectories of specific body parts, the silhouette of the tracked bodies, and the captured depth image. At layer 1 data is captured by an array of virtual sensors, associated to a broad range of physical sensors, including motion capture, video cameras, microphones, and physiological sensors. We characterize each virtual sensor with its sampling rate and with the data it provides (e.g., an image, a 3D position, an acceleration, a numeric sample, an audio or a physiological signal). Data is processed to get representations suitable for the next analysis layer. Table 1 presents a list of possible outputs of layer 1.

Layer 1 - Physical signals **Data from virtual sensors and signal conditioning**	
Trajectories	Positional data (e.g., 2D or 3D positions of joints, and of the barycenter) obtained from MoCap, video cameras, and RGB-D sensors (e.g., Kinect).
Bounding Space Convex Hull	The minimum polygon (2D) or volume (3D) surrounding an input cloud of points (MoCap) or a body silhouette.
Accelerations	Measures from accelerometers and gyros.
Physiological sensors data	EMG, EEG, ECG, and so on.
Respiration	Signal from specific respiration sensors or from a microphone.
Nonverbal vocal utterances	E.g., *kiai* in Karate, vocal utterances in dance.
Floor feet pressure	Measure of physical weight on each foot from a sensitive floor.

Table 1. Physical signals (virtual sensors).

Layer 2 – Low-level features: Time-series

Layer 2 (*Low-level features*) receives the raw data from the array of virtual sensors at layer 1 and extracts a collection of features characterizing movement locally in time. That is, low-level features are usually computed instantaneously on the raw data or on small buffers of a few samples by using a sliding-window approach with maximum overlap. Thus low-level features are represented as time-series having usually the same sampling rate as the raw data they are computed from. Time-series may be either univariate (e.g., kinetic energy) or multivariate (e.g., the x, y, and z components of velocity). Table 2 shows a (non-exhaustive) list of low-level features at layer 2.

Layer 2 - Low-level features **Time series of instantaneous descriptors of movement**	
Kinematics	Velocity, acceleration, and jerk.
Gravity	Acceleration toward the ground.
Kinetic Energy	The kinetic energy of a cloud of 3D moving joints, possibly weighted by their masses, using weights from biometric tables.
Motion Index or Quantity Of Motion (QoM)	Area of the difference of the areas of silhouettes computed on consecutive frames [7].
Postural Contraction	A measure of the extent at which body posture is close to its barycentre.
Postural Symmetry	Geometric symmetry of a posture with respect to a plane or an axis.
Smoothness	A joint moving according to the specific laws from biomechanics defining smoothness [15].
Postural and Dynamic Balance	Computed from (i) the measure of the projection to the floor of the barycentre of the body in the area defined by the feet and (ii) the ratio between acceleration of the barycentre of the head and of the barycentre of the body.
Change of Weight between Feet	Computed from pressure patterns measured by a sensitive floor.
Postural Tension	A vector describing the angles between the adjacent lines identifying feet (the line connecting the barycentre of each foot), hip, trunk, shoulders, and head directions. This is inspired by classical paintings and sculptures where such angles are exploited to express postural tension.

Table 2. Low-level features.

For example, Gravity, i.e., acceleration toward the ground, is a layer 2 feature, consisting of a time-series of data obtained with an accelerometer or with motion capture, and which is the basis for measuring the Lightness mid-level feature at layer 3.

Layer 3 – Mid-level features: Trajectories or points in multidimensional (amodal) spaces

Whilst analysis at layer 2 is local in time, layer 3 (*Mid-level features*) deals with structural aspects, i.e., it computes features describing one single movement unit. If movement units cannot be identified (e.g., in a continuous stream of tightly interlaced movements), layer 3 operates on time windows, long enough to grab movement time evolution.

Furthermore, features at layer 3 are at a level of abstraction such that they represent *amodal* descriptors, i.e., the level where perceptual channels integrate. This means that, for example, *Fluidity* is a meaningful feature to characterize both audio and movement. Amodal descriptors enable the design of mapping strategies from movement to the sonic domain: we can analyze a movement starting from physical signals (layer 1) up to layer 3, and then we can map features at layer 3 back down to the physical signal in the sonic domain. This is a fundamental step in our DANCE Project, enabling multisensorial translation of movement qualities to another sensorial domain, namely the sonic one.

Analysis and processing at layer 3 goes through two basic steps: segmentation and computation of amodal features.

Segmentation. The segmentation step identifies the analysis unit. This can either be a single movement unit (a gesture) in a stream of movements or a time window of a defined duration. In the former case segmentation may operate at different levels, that is, a movement unit may be, e.g., a single movement or a whole phrase. Depending on how segmentation is performed, layer 3 produces different outputs. If single movement units are isolated, these are conceived as events. This means that it is not possible to determine a sampling rate anymore. Rather each single event is associated with a given time (typically the time instant when the movement unit ends). An array of values of features is associated with each of such events, that is, the output of layer 3 is a position in a multidimensional feature space i.e., a location in a multidimensional map. If, instead, analysis is still performed on time windows, such windows are either not overlapped or partially overlapped. A sampling rate can still be determined, based on windows duration and overlap, and an array of values of features is computed for each time window. In this case, the output of layer 3 is a trajectory in a multidimensional feature space, i.e., a path in a multidimensional map. Features computed at layer 2 are usually employed to perform segmentation. One of the simplest techniques consists in analyzing kinetic energy by applying a possibly adaptive threshold. More sophisticated techniques exploit, e.g., machine learning approaches where a vector of values obtained by applying analysis primitives to layer 2 time-series is used to train and feed recognizers to distinguish pauses and movements. In case real-time analysis is not needed and an archive of performances is available, manual annotation can be carried out when automatic segmentation is not accurate enough.

Layer 3 - Mid-Level Features **Trajectories or points in multidimensional spaces**	
Contraction	Movement contracting along time.
Dynamic Symmetry	Symmetry of movement features, also in terms of analysis primitives, e.g., symmetry of entropy between left and right hand [14].
Directness (Laban's *Space*)	Movement to directly reach a target position (Direct vs. Flexible) [28].
Lightness (Laban's *Weight*)	How gravity influences a movement, e.g., based on relations between vertical and horizontal components of acceleration.
Suddenness (Laban's *Time*)	Rapid change of velocity (Sudden vs. Sustained) in a movement.
Impulsivity	Movement which is sudden and not prepared by antagonists muscles [19].
Equilibrium	The extent at which a movement is balanced, i.e., the tendency to fall or to keep a stable balance.
Fluidity	A fluid movement [23] is smooth and coordinated (e.g., a wave-like propagation through body joints).
Repetitiveness	The extent at which a movement exhibits repetitive patterns.
Tension	The extent at which a movement exhibits rotation of multiple planes, including spirals (computed from Postural Tension).
Cohesion	Whether a movement is made of components exhibiting similar features (e.g., tendency of limbs to move as a single entity in a direction).
Coordination	Whether a movement is made of synchronized components (e.g., synchronization of limbs to operate a body at the unison). This corresponds to temporal entrainment in a group.
Origin	Whether a movement originates at a joint, and at what extent a joint leads the body in the movement. This may correspond to leadership when measured in a group.
Attraction	The degree of influence an external point in space has on movement (e.g., like a magnet attracting or repulsing the dancer).
Slowness	Whether a movement is continuous and at an extremely slow speed.
Stillness	Pause: minimal movements depending on physiology (e.g., respiration), emotions, and attention continuously occur.

Table 3. Mid-level features.

Computation of features. Two major approaches are applied for computing mid-level amodal features:

1. Direct computation of mid-level features specifically defined and grounded on low-level features and/or physical signals (e.g., Smoothness is involved in the computation of Fluidity). Table 3 introduces a list of mid-level features at layer 3.
2. Application of *analysis primitives* to one or many low-level features. Unary operators can be applied, e.g., to retrieve salient events [20] (for instance, peaks and valleys in the time-series of kinetic energy), and to estimate the complexity of a movement by computing, for example, sample entropy [25] on one or more time-series of low-level features (see e.g., [13]). Binary and n-ary operators can be applied e.g., for measuring the relationships between time-series of low-level features computed on the movement of different body parts (limbs). For example, synchronization techniques are applied to evaluate coordination between hands (the so called intra-personal synchronization) or coordination of dancers in a group (i.e., inter-personal synchronization). Causality provides information on whether, for example, the movement of a joint leads or follows the movement of another joint in the body, or it can even explain the leadership of a dancer or of the movement of a musician in a group [13][14]. Predictive models are applied, e.g., to estimate the extent at which actual movement corresponds to or violates expectations (i.e., something related to tension, see e.g., [6]).

Layer 4 – Expressive qualities

Whilst the previous layers focus mainly on features at a growing level of abstraction from layer 1 to layer 3, this layer mainly focuses on the **nonverbal communication of movement qualities to an external observer**. *Memory* and *Context* are factors that intervene mainly at this layer, characterized by observation within layered and longer time intervals. Both Memory (the history of previous movement qualities) and Context may influence how an external observer perceives and interprets a feature in terms e.g., of expectancy [6], saliency (unexpected, rare, or contrasting movements may contribute to raise sensitivity to specific movement features), and sensitivity (stillness may raise sensitivity to very tiny movements). These factors may be modeled as possible biases in the measure of a feature to get a refined measure that better reflects the perceived quality of a movement.

At layer 4, machine-learning techniques are often employed to map a point or a trajectory in a multidimensional space, obtained at layer 3, onto the movement quality an external observer perceives. Both supervised and unsupervised approaches were adopted in the literature. Considering, e.g., communication of emotion, existing studies applied for example clustering [14], support vector machines [22], and several ways of integrating and fusing different classifiers (e.g., see examples in [18]). Whereas, on the one hand machine learning cannot be simply taken as the solution to whatever problem and should be accurately tailored to the problem under investigation, on the other hand the above-mentioned examples and a growing body of literature [17][18] show that machine learning is a viable and suitable approach to the analysis on nonverbal movement qualities.

Layer 4 - Communication of expressive qualities	
Predictability/expectancy	The extent at which an external observer can predict a dancer's movement [6].
Hesitation	When an external observer cannot clearly perceive a movement intention.
Attraction / Repulsion	The extent at which an external observer is attracted/repulsed.
Groove	The extent at which dancer's movement elicits movement in an external observer.
Saliency	A movement which is perceived as salient with respect to others occurring at the same time.
Emotion	The emotion, expressed by full-body movement and posture, which is conveyed to an external observer. Emotions can be represented either in a categorical way or by means of dimensional models (e.g., PAD). See, for example [14][22].
Nonverbal social signals	Entrainment in its temporal and affective components [21][27], leadership [27], and so on.

Table 4: Communication of expressive qualities

COMPUTATIONAL MODELS AND SYSTEMS

Our conceptual framework aims at providing a solid ground to build computational models and systems upon. In the DANCE Project we started implementing the framework in the EyesWeb XMI software platform (www.infomus.org).

With respect to physical signals (layer 1), we implemented a scalable platform, supporting input devices ranging from motion capture, respiration, and other physiological sensors (typically used for research purposes and lab experiments), to RGB-D sensors and wearable devices (for applications in the wild). A typical configuration for a real-time application is based on 5 wireless accelerometers on wrists, ankles, and coccyx (body barycenter).

With respect to low-level features (layer 2), most of them (see Table 2) were already available in EyesWeb and are included in the DANCE implementation of the framework.

Concerning mid-level features (layer 3) and expressive qualities (layer 4), some existing EyesWeb libraries were reconceived and novel analysis modules were added. Existing modules that were reconceived include e.g., those for measuring Contraction, Dynamic Symmetry, Directness, and Suddenness. New modules include, e.g., computational models for the analysis of Fluidity, based on a physical spring-mass model, as described in [23], and modules for the analysis of Impulsivity, as described in [19]. Future work will focus on the analysis and investigation of features at layer 3 and of expressive qualities at layer 4. Some features in Table 3 (e.g., Tension, Origin, and Lightness) still need some extensive research and development work. This paper, however, focuses on the framework and a broad discussion of each feature and of each movement quality would go far beyond its scope.

SONIFICATION OF DANCE PERFORMANCES

Our research is inspired by the intersection of art and technology [3]. We are using the conceptual framework and its implementation for designing interactive sonifications translating movement qualities into the sonic domain. The work is carried out in collaboration with composers Pablo Palacio and Andrea Cera. Demonstrations were publicly presented at two major events in 2015 (the STARTS EU Workshop, Bozar, Brussels, Belgium, and the SONAR+ festival, Barcelona, Spain), showing the effectiveness of the approach[2].

An initial repository of multimodal recordings of movement qualities has been also collected and made available (see our other paper in these proceedings). Further, we are currently working with several choreographers and dancers in order to refine the definitions of the features and qualities included in the conceptual framework: for example, a paper in preparation presents a novel definition and software module to analyse Lightness. Further qualities are currently under analysis, also inspired by the expressive vocabulary of choreographers collaborating in DANCE.

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[2] https://www.youtube.com/playlist?list=PLEVgkiAQI8zIFbTFv8I7ioEpuDHNbYsdC

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