Analysis of Dominance in Small Music Ensemble

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ABSTRACT

This study addresses the application of the Multi-Scale Fuzzy Entropy Analysis to investigate dominance in small music ensemble. Taking a string quartet as the case for study, it confirms and extends previous results found in [8] revealing that dominance over others may be achieved through the regulation of individual and group's behavior complexity.

Categories and Subject Descriptors

H.5.5 [**Information Interfaces and Presentation**]: Sound and Music Computing

General Terms

Experimentation

Keywords

dominance, behavior complexity, music ensemble

1. INTRODUCTION

This research aims to model the behavioral traits in dominance, taking a small music ensemble such as a string quartet (SQ) as a test-bed. The development of computational models capable of explaining and analyzing social behavior in real time, in particular, dominance or leadership, may lead to new multimedia systems such as embodied social media and user-centric media.

This research stems from the results obtained in [8]. We observe the movements of the musicians in the ensemble, specifically, their head movements, and also motion within the group as a whole. The technique proposed in this paper is based on the Multi-Scale Fuzzy Entropy Analysis [1] , designed for real-time modeling and analysis of the behavioral complexity of the SQ, on the basis of individual musicians' head movements as well as group movement features. The latter are derived from characteristics of the polygon formed by the barycentres of the heads of the four musicians

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2. RELATED WORK

Based on observational studies, Burgoon and Dunbar defined dominance as a set of "expressive, relationally-based strategies and as one set of communicative acts by which power is exerted and influence achieved" (p.362, [3]). Dominance can thus be distinguished through individual and relational behavioral traits that reveal one person's capacity to influence the outcomes of a group interaction [3].

A number of ways of automatically identifying patterns of dominance have been proposed by the emerging social signal processing (SSP) community. Research has mainly been conducted on face-to-face interaction (e.g. conversation) in formal settings like talk shows or professional meetings (for a review, see [10, 5]). Speech-related features (speaking time, number and length of turn-taking) have been revealed to be the most effective means of distinguishing dominant people [5]. A few multi-modal approaches have successfully coupled audio and vision-based features to improve recognition rates integrated gaze behavior and employed basic movement-based features (e.g. amplitude and length of movements) [13, 11].

By contrast, attempts to automatically model behavioral traits of dominance in string quartet (SQ) are rare and consider non-verbal expressive behaviors of musicians [15, 8]. Research on social interactions in music ensemble has mainly focused on leadership through case studies using observations and interview methods [12, 7]. Leadership refers to one's capacity to guide people by means of his social and organizational skills [9]; trait-centered approaches to leadership may include dominance as one possible feature.

Recent observations of SQ rehearsals show that the regular presence of a leader may ensure group cohesion and facilitate the collaborative-music making process [7]. An apparently paradoxical result as roles seem to be distributed in an egalitarian way among the musicians (first and second violins, viola and cello). Leadership in a SQ can occur at three different levels:

(i) *social status*: the first violin has often been referred to as a leader in western classical music [7];

(ii) *musical structure*: as noted by Gilboa and Tal-Shmotkin, the SQ being a musically-driven "working out process", the roles of musicians may actually change over time as demanded by music score (e.g., fugato style versus coordinated repeated staccato) [7]. The music score, defining the theme passing from one voice to another in the SQ, might contribute to define a sort of "ground truth" on this perspective of leadership.

(iii) *performance practice*: Studies focusing on the internal dynamics of string quartets in rehearsal show that they exhibit subtle variety of "leadership patterns" [7]. King identified team roles that characterize the various types of interactions between co-performers (the means musicians have to predict and react to the behavior of other member in the ensemble e.g., *leader*, *deputy-leader*, *distracter*, etc.) [12]. Briefly said, the SQ presents an experimental situation of interest where the need for a stable leadership has to be reconciled with the flexibility necessary for teamwork.

By analyzing dominance, a component of leadership at the performance level, we address in more detail the process by which one (musician) can impact upon interactions between the other players during the performance

3. EXPERIMENT

3.1 Participants

The experiment took place in a 250-seat auditorium, an environment similar to a concert hall, suitable for experiments in ecological setups. A multimodal setup was created to capture and analyze the movement, audio, and physiological data of the professional *Quartetto di Cremona* SQ. The analysis presented in this paper concerns the time series data of the musicians' heads movements. Each player wore a white hat, on the top of which was mounted a green passive marker, whose trajectory was captured by means of a top-view video-camera (60 fps). Standard video tracking techniques were employed to extract the position of each heads' center of gravity (COG)(see Figure 1). Original x and y components were roto-translated with respect to each of these reference points in order that the data data for analysis corresponded to the displacement of each head in the anterior-posterior (AP; forward/backward) and mediolateral (ML; right/left) directions respectively. Following the recommendations in [14], analysis was conducted on the increment of the roto-translated position time series, to limit the effects of data non-stationarity.

Head movements are known to play a central role in the implicit communication strategies devised by musicians to coordinate with one another both at rhythmic and expressive levels [8]. In addition, a polygon delineated by the four COGs of the musicians' heads was identified in order to model the entire group as a whole entity [8], see Figure 1 and demo at:
`ftp://ftp.infomus.org/Pub/ftp-user-root/`
`Siempre/quartetcomplexity.avi`.

3.2 Stimuli

The SQ was asked to perform the first movement (*Allegro*) of the String Quartet No. 14 by Franz Schubert. Five performance conditions were selected in order to emphasize variations in the social interaction: (i) *Training* condition, a rehearsal-like performance aimed at studying performance practice; (ii) *Switch* condition, the first and second violinists were unexpectedly asked to swap parts soon before the recordings. This condition was devised specifically to distinguish between the influence of the music parts themselves and social interaction during performance; (iii) *Functional* (or metronome) condition, a strongly constrained rehearsal-like performance in which players were instructed to follow an external audio steady pulse to ensure rhythmic accuracy (forcing of an external leader, the metronome); (iv) *Regular* (or concert) condition, a concert-like performance (without an audience), putting into practice, at best, all the usual mechanisms and techniques that the quartet have learned and honed; (v) *Over-expressive* condition, a rehearsal-like performance where musicians were instructed to amplify expressive timing and dynamic variations (higher degree of cohesion possibly required).

This study focuses on the musical extracts in which the first violin is a clear protagonist with respect to the other musicians (e.g., *canto accompagnato*, a common string-quartet texture in 17-18th musical style).

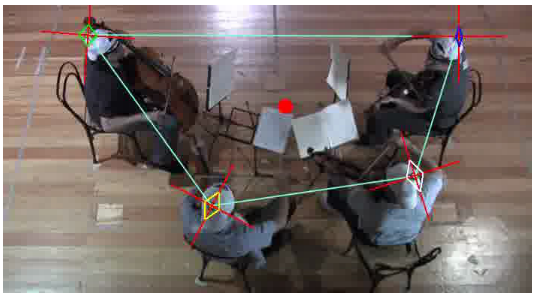

Figure 1: Visualization of the polygon relating the four musicians' heads and the complexity index along the anteriorposterior (AP) and mediolateral (ML) directions

4. MULTI-SCALE FUZZY ENTROPY ANALYSIS

Analysis of dominance is based on the theoretical framework of Multi-Scale Entropy (MSE), a non-linear technique initially developed by [2] and improved by [1, 16] to quantify the behavior complexity, i.e., the information expressed by the body movement dynamics over multiple time scales.

Considering a time series, the computation of a Complexity index (C_I) comprises three distinct processes deriving from the Multi-Scale Entropy method:

1. a coarse-graining procedure to represent the dynamics of the system at different timescales [2]

2. the quantification of the degree of irregularity of each coarse-grained time series through the application of Fuzzy Sample Entropy (FSampEn) [1, 16]

3. A complexity index (C_I) of the time series is calculated by integrating the FSampEn values obtained for the different time scales.

The heads of the musicians in the SQ form the four corners of the polygon (see Figure 1). Thus, the algorithm for identifying the dominant member of the group takes input data from the four vectors which denote the speeds at which the musicians' heads move, and also from one other vector, which denotes the speed at which the center of gravity of the polygon moves. The latter gives an approximate value for the group activity overall.

We propose an algorithm to identify the dominant musician, summarized by the following steps: (i) computing the Complexity Index (C_I) for each vector component (ii) selecting the musicians displaying the lowest C_I (*potential dominant*) (iii) computing the Pearson's product moment correlation of the C_I of each potential dominant with the C_I of the polygon center of gravity (iv) selecting the musicians displaying the highest positive correlation (*dominant*).

5. RESULTS

5.1 Bias of the music score

To disentangle the effects of structural features of the music as distinct from the interpersonal dynamics within the group, an analysis of the complexity of the musical score was carried out. It could be argued that the behavioral complexity observed during the experiment may be a product of the complexity of the musical task faced by each musician when playing (e.g. density of notes, intervals). For each of the five extracts of Schubert's Quartet played in the experiment, the individual musicians' parts were evaluated using the expectancy-based model of melodic complexity [4]. Based on the variety of intervals, and the rhythmic and melodic densities encountered in each of the parts, for each musician, a unique index is given. Friedman's nonparametric repeated measure analysis of variance was conducted to compare the melodic complexity index between musicians, over the five extracts. No significant effects were found (Exact p=.630): the level of melodic complexity can be considered similar for each musician. Thus, it is logical to claim that differences in the complexity of musicians' behavior are related mainly to expressive and social behavior, rather than score-based properties. Thus, it is logical to claim that differences in the complexity of musicians' behavior are related mainly to expressive and social behavior, rather than score-based properties.

5.2 Complexity Index

Analysis was conducted on the Complexity index (C_I) of musicians'head velocity along the roto-translated component x and y (leftward/rightward and backward-forward movement). Considering the eight observations available for each musician in each condition, the presumed normality of variance was not met and a Friedman's nonparametric repeated measure analysis of variance was used to compare musicians'C_I across conditions [6]. Exact tests were performed, and, if the results were statistically significant, adequate post-hoc analyses were performed. A measure of effect size (r) was also computed for pairwise comparison.

Differences between musicians (Complexity Index)	
C_{I_x}	*m1*<*m2** (r= .80); *m2*<*m3** (r= .74)
C_{I_y}	*m1*<*m2** (r=.58),*m3** (r=.41),*m4** (r= 1)

*p < .0167 (Bonferroni-corrected alpha value)

Table 1: Post-Hoc analyses to assess significant differences between musicians in the *training*, *normal* and *overexpressive* conditions. C_{I_x} and C_{I_y} refer to the Complexity index of their head movement along the component x and y respectively; *m1, m2, m3* and *m4* refer to the first violin, second violin, viola and cello respectively.

Significant differences between musicians were found in the data from the three experimental conditions concerning expressivity (*training, regular, overexpressive*), Exact p = .001 in both cases related to C_I of components x and y respectively. Results of post-hoc analyses are indicated in Table 1 and represented as a graph in 2.

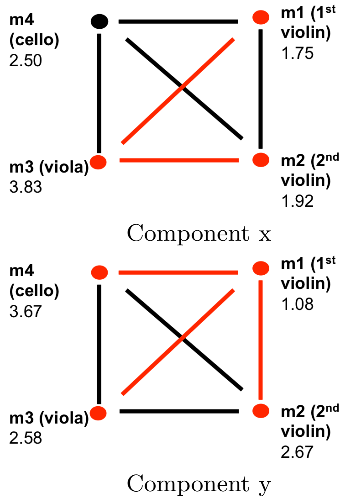

Figure 2: Each node represents one of the four musicians and shows the sample average rank of its Complexity index (C_I) for the three conditions: *training, normal, overexpressive.* The figures on the top and the bottom show the values for the x and y components of head movement respectively. Red lines indicate significant differences between the musicians (nodes).

5.3 Polygon's correlation

Pearson's product moment correlation was computed to assess the relationship between those Complexity Index (C_I) values recorded for each musician and those obtained from variations in the center of gravity of the polygon. Results from the *training, normal* and *overexpressive* conditions are indicated in Table 2.

correlation between polygon and musicians				
	m1	*m2*	*m3*	*m4*
C_{I_x}	**0.34**	**36**	-.27	-.08
C_{I_y}	**.54**	**.54**	-.14	-.10

Table 2: Pearson's correlation between C_I values of musician's head movement and those of the center of gravity of the polygon that model the entire group as a whole entity; for component x and y respectively.

6. DISCUSSION

Empirical evidence shows that the Complexity index values of the first violinist's mediolateral (left/right) and especially anterior-posterior (forward/backward) movements are lower than those of the other musicians in performance conditions where expressivity is unconstrained or enhanced and where the usual roles within the ensemble are maintained (*training, normal, overexpressive* conditions). To a lesser extent, the second violinist tends to show lower Complexity index values for mediolateral (left/right) movements in the same conditions.

On one hand, these results confirm and refine those found in [8] regarding the first violin's behavior complexity. Not only do they provide an overall value for head movement complexity, but also, they indicate in more detail the favored axis direction within which that movement occurs over the performance as a whole (here, mainly within the forward/backward axis). On the other hand, these results suggest that the second violin may emerge as an alternative dominant player to the first violin, as the corresponding complexity values are also significantly low. The correlational analyses may support the peculiarity of the first violinist's behavior with respect to the others. The positive correlation of the first violin's Complexity index values and those of the center of gravity of the polygon in both axes showed that the variations in the behavior of the first violinist were strongly associated with those of the group and had the same valency (i.e., as one increased, the other increased, too). For the other musicians, the associations tended to occur in the opposite direction and for the viola and cello, they were weaker.

The two behavioral characteristics indicating dominance in a SQ might be understood as follows: low complexity in the first violinist's behavior may increase its predictability for others. This also implies that real-time musical decisions, such as impulsive anterior-posterior (front-back) head movements to cue simultaneous full-ensemble entries attacks, for example, will be highly salient. The low complexity of the movements of the second violinist should also highlight his candidacy as an alternative dominant player. From this perspective, these results might be seen to confirm observations made by [12]], in which leadership is assumed by the first violin in association with the second violin (as deputy leader) Correlations between data observed for the first violin and those observed for the polygon representing the SQ group activity, highlight that dominance requires the ability to regulate the activity of others.

7. CONCLUSION

Results confirm the hypothesis that the musician whose movements yield the lowest Complexity Index and the highest correlation with the group activity is, correspondingly, the dominant player. These findings are consistent with previous observations made using other data on SQs and a different technique [8]. In addition, the application of the application of the Multi-Scale Fuzzy Entropy Analysis method shows an increased robustness to noisy values, typical of human behavioral data. We implemented the technique presented in this paper as a software module in the Eyesweb XMI real-time platform (www.eyesweb.org). This enables researchers to measure and analyze dominance features in small groups in real-time.

Future research directions include: (i) investigating this method using data captured at higher frame rates and higher resolution, including motion capture data, to compute the complexity index on larger time-scales; (ii) to integrate individual behavioral features developed by [11] to approximate motion activity and to implement further expressive features, e.g. impulsivity, contraction/expansion, orientation of the face and trunk of each musician - to better evaluate group activity based on polygon geometric variations; (iii) to devise post-performance questionnaire to assess the observed behavioral data with subjects explicit responses after each experiment session.

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