Multi-Scale Entropy Analysis of Dominance in Social Creative Activities

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ABSTRACT
Our research focused on ensemble musical performance, an ideal test-bed for the development of models and techniques for measuring creative social interaction in an ecologically valid framework. Starting from expressive behavioral data of a string quartet, this paper addresses the application of Multi-Scale Entropy method to investigate dominance.

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

General Terms
Experimentation.

Keywords
Multi-Scale Entropy, embodied social interaction, music performance.

1. INTRODUCTION
The analysis of social dynamics is receiving an increasing interest from the ICT research communities. User centric media and social networks have widened the possibilities for communication. Innovative form of collaboration where the usually passive consumer evolves toward active prosumer is developed [22]. Networked media applications enable groups of users to collaboratively explore audio/video content through their physical expressive movements [1].

A central issue related to the study and modeling of social interactions is hierarchy formation and in particular establishment of dominance [21]. Coordination of individuals involved in joint activities sharing common objectives may be fostered when roles are clearly distributed within a group [13].

A major research topic at our institute is the automated analysis of expressive non-verbal behavior: in particular, we focus on the modeling of expressive and creative social interactions, the dynamic processes that lead to the establishment of dominance within a group. Recent research concerns the analysis of social interaction in small groups of users with a particular focus on aspects related to computational models and techniques for real-time measuring of synchronization and dominance: for example, Varni and colleagues [19] analyzed the emergence of synchronization and dominance in a violin duo performance, adopting an approach centered on the modeling of the duo as a complex system whose phase synchronization is computed based on Recurrence Quantification Analysis (RQA). Recently, Varni and colleagues [18] extended such an approach to the analysis of synchronization and dominance in a string quartet, and applied their method to the data obtained from the same experiment data of this paper. The work presented here, however, substantially differs from the work in [18] since we address a different aspect of dominance (i.e., dominance as a feature related to complexity rather than dominance as a feature related to anticipation). Moreover, the analysis in this paper is based on the theoretical framework of multi-scale entropy (MSE), whereas [18] focuses on chronemic approaches.

The emerging community of social signal processing (SSP) has conducted research on conversation, in formal settings like talk shows or professional meetings [20],[8]. Our paper considers a social scenario in which non-verbal co-creation and expressiveness are the core elements: the joint music performance of a string quartet. Music performance is one of the fundamental examples of non-verbal human activities that is above all interactive, creative and social. Two further advantages advocate for music as experimental test-bed for analysis of dominance: (i) music score offers the experimenter a ground truth that explicitly identifies leadership or at least the major protagonists (e.g., the first violin in a quartet playing the melody and the others musicians accompanying), (ii) in literature, there is evidence on the role of body in music and in particular on its communicational aspects that support the identification of suitable behavioral variables for the analysis of social interactions (e.g., head movements).

Research presented in this paper aims at testing hypotheses on emergence of dominance in a music ensemble, starting from the analysis of the complex dynamics of the musicians body movements, based on MSE, a non-linear technique developed by Costa et al. [4] to quantify the multi-scale variability of the signal over a range of time scales. In particular, MSE is here used to test the hypothesis that the behavior of the leading musician (or, more in general, of the leading participant in a small group) is less complex than the behavior of the other musicians (participants).

MM'10, October 25–29, 2010, Firenze, Italy.

2. EXPERIMENT

2.1 Participants

A string quartet was selected to investigate social interaction in a small group. Before the experiment, feasibility studies have been carried out with several famous quartets visiting our center. The experiment took place with the renowned Quartetto di Cremona in the 250-seat auditorium, an environment similar to a concert hall, particularly suited for experiments in ecological setups. A multimodal setup was created to capture and analyze movement, audio, and physiological data of musicians [18]. Preliminary analysis presented in this paper concerned the time series of the musicians' heads movements (position and velocity). Each player wore a white hat including a green passive marker, which trajectory was captured by means of a top-view video-camera (60 fps). Standard video tracking techniques were employed to extract the heads center of gravity (COG) in both anteriorposterior (AP) and mediolateral (ML) directions. The Euclidean distance between consecutive points was then computed to obtain a mono-dimensional signal characterizing the head movements. Following recommendations by [14], analysis was conducted on the increment of the original COG position time series (or differenced time series) to limit the effects of data non-stationarity. The velocity time series were obtained by calculating the differences between consecutive data points of the sway time series.

Head movements are considered to play a central role in the expressive regulation of music performance since they indicate specific moments during the performance requiring synchronized start [7] or because they convey emotional states that facilitate interpersonal coping [6]. According to [11], a polygon individuated by the musicians head COGs was further identified to model the entire group as a collective rather than focusing on each individual separately.

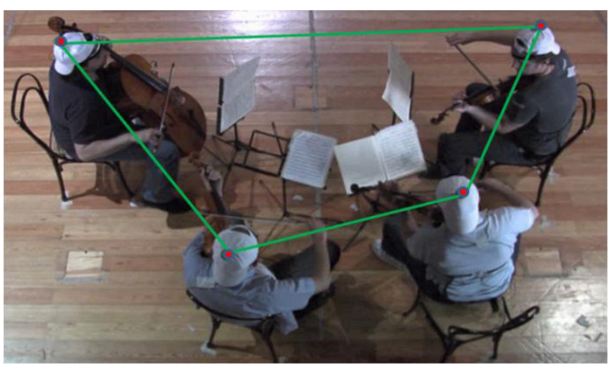

Fig.1. The renowned string quartet Quartetto di Cremona during the experiment captured from the top-view video camera. Each musician wears a white hat including a green passive marker. The figure shows the COGs of the heads and the polygon connecting them.

2.2 Stimuli

Musicians were asked to perform the first movement (*Allegro*) of the String Quartet No. 14 in D minor, known as *Death and the Maiden*, by Franz Schubert. Five performance conditions, repeated twice, were defined aiming at exploring distinct levels of coordination among musicians: (i) *training* condition, a rehearsal-like performance aimed at studying performance practice (ii) *switch* condition, a swap of the musical score of the first and second violin was unexpectedly proposed soon before the recordings, (iii) *functional* (or *metronome*) condition, a rehearsal-like performance with the strong constraint to follow an external audio steady pulse to force musicians playing rhythms accurately, (iv) *regular* (or *concert*) condition**,** a concert-like performance (without an audience), (v) *over-expressive* condition, a rehearsal-like performance where musicians were instructed to amplify expressive timing and dynamic variations. Our analysis focused on two music segments (length of about 50s), where, according to the score, the first violin is in a *protagonist/dominant* position with respect to the other musicians (e.g., "*canto accompagnato*" where the first violin plays the melody while the others are accompanying by producing repetitive chords altogether).

2.3 Hypotheses and Methodology

Our analysis followed the approach by [4], termed multi-scale entropy analysis (MSE), to define a complexity measurement that focuses on quantifying the information expressed by the body movement dynamics over multiple time scales At each level of resolution, the multi-scale entropy algorithm yields a value that reflects the mean rate of creation of information [4]. Multi-Scale Entropy has been used for analysis of physiological data such as heart rate variability [4], for postural analysis [5], and for emotion recognition [12].

In this paper, the MSE method was used to test two hypotheses related to the establishment of dominance (*leadership*): (i) the times series of the COG velocity obtained from the leading musician is less complex than those obtained from other musicians; (ii) the complexity of the leading musician COG sway velocity best correlates with the complexity calculated from the variations of the polygon's area that relate musicians' heads.

The MSE algorithm comprises two distinct processes : (i) a coarse-graining procedure to represent the system's dynamics at different time scales, and (ii) the quantification of the degree of irregularity of each coarse-grained time series through the application of Sample Entropy (SampEn), a statistic introduced by [15]. Sample Entropy computes the negative average natural logarithm of the conditional probability that subsequences similar for *m* points in the time series remain similar (as defined by Eq. 1) when one more point (*m*+1) is added to those sequences. Small values of SampEn indicate regularity. Similar subsequences (or *template vectors*) of length *m* within the times series are estimated by the correlation sum n_i^m (see Eq (1)):

$$n_i^m = \frac{1}{N-m-1} \sum_{j=1, j\neq i}^{N-m} \Theta\left(r - \left\|u_i(m) - u_j(m)\right\|_\infty\right) \quad \text{(Eq. 1)}$$

where $u_i(m)$ and $u_j(m)$ are the template vectors of length *m* formed from the standardized original times series, at time *i* and *j* respectively, *N* is the number of samples in the time-series, *r* is the tolerance (or *radius*), Θ is the Heaviside function, and $\|\|_\infty$ is the maximum norm.

2.4 Selection of parameters

Dimension *m* and tolerance *r* of SampEn were fixed respectively to 2 and 0.15 following previous studies dealing with postural analysis [5],[14]. To ensure enough samples for the analysis, approximately 3000 data samples obtained from each recording were coarse-grained up to scale 6. The shortest coarse-grained time series comprised 500 data points. A complexity index (C_I) of a time series was calculated by integrating the SampEn values obtained for the six scales.

3. RESULTS

3.1 Shuffled surrogate data tests

The presence of non-linearity in the original times series was checked out by applying the method of surrogate data. Following [16], we tested the null hypothesis that the underlying process of the COG velocity time series correspond to an uncorrelated noise. The tests were performed by randomly shuffling the samples of velocity time series and then estimating the *complexity index* results for these *shuffled* surrogate sequences, keeping the original input parameters m and r of the Multi-Scale Entropy (MSE). Highly irregular time series are produced by randomizing the time order of a dataset. This procedure does not affect the mean and standard deviation but removes temporal correlations and potential nonlinear interrelations. For each musician and condition, 39 surrogates of the original times series were generated. The surrogate complexity index values was compared to the original ones by conducting a two-tailed rank-order test and resulted significantly lower than the original ones. The null hypothesis of an uncorrelated random process could then be rejected.

3.2 Nonparametric Friedman tests

Given that at least four observations were available for each musician in each condition (see Fig. 2), assumption of normality of variance was not met and Friedman's nonparametric repeated measure analysis of variance was used to compare musicians' Complexity Index across conditions. Unfortunately, factorial analyses are not available for ordinal data, but we may hypothesize some kind of interaction effect if results differ across conditions. Exact tests were performed, and, if statistically significant, adequate post-hoc analyses were performed (see, e.g.,[9]). A measure of effect size (r) was also computed: values lower than .10 indicate a negligible effect, from .10 to .30 a small effect size, from .30 to .50 a moderate effect size, and higher than .50 a large effect size [3]. Given that five Friedman's tests were performed, the comparison-wise level of significance was corrected to .01 to avoid Type I Error rate inflation. According to this value, significant differences were found only in the Train condition (Exact p = .007, r = .61). Post-hoc analyses revealed that Musician 1 and Musician 4 did not differ among them, but had significantly lower Complexity Index than Musician 2 and Musician 3 ($p < .01$, $r = .55$ in either case). Marginally significant results were found also in the Metronome and the Overexpression condition (Exact p = .036, r = .45 and Exact p = .033, r = .46, respectively). In the former case, Musician 1 showed lower Complexity Index than Musician 2 ($p < .01$, $r = .68$) than Musician 3 ($p < .05$, $r = .41$), and Musician 4 showed lower Complexity Index than Musician 2 (($p < .05$, $r = .41$). In the Overexpression case, Musician 1 and Musician 4 did not differ but had significantly lower Complexity Index than Musician 2 ($p < .01$, $r = .62$ in either case) and Musician 3 also tended to have a lower Complexity Index than Musician 2 ($p < .05$, $r = .41$). No difference was found in the Switch and in the Concert condition (Exact $p = .754$, $r < .10$ and Exact $p = .355$, $r < .10$, respectively).

3.3 Polygon's correlations

In order to assess the association of the Complexity Index values of each musician with the ones obtained from the variations of the polygon's area that that relate musicians' heads, Pearson's product moment correlation was computed. Results showed a positive association between Musician 1's Complexity index values and Polygon's ones (r=.62). Correlation with Musicians 2, 3, and 4 were r=-.51, r=-.21, and r=-.16. respectively.

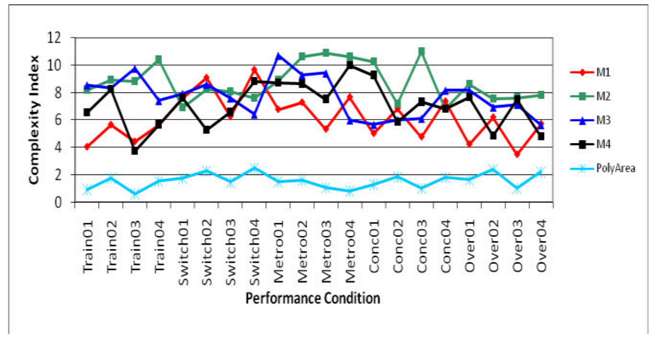

Fig. 2: Complexity index results for the four musician across all five experimental conditions.

4. DISCUSSION AND CONCLUSION

Empirical evidence shows that Musician 1 and, to a lesser extent, Musician 4, tend to show lower Complexity Index values, but this is not true in all conditions. These results seem to suggest that the experimental scenario may moderate Complexity Index differences among musicians. The hypothesis of a possible interaction effect of performance conditions on the Complexity Index should be tested on more data with a factorial ANOVA. These results may also suggest that Musician 4 may emerge as an alternative leader as the corresponding complexity values are also significantly low. However, our evidence shows that he moves much less that Musician 1, and his Complexity Index value is only weakly correlated with that of the polygon's area. Results from the Switch condition further suggest that the music score by itself may not be sufficient as an explaining factor [7]. Musician 2, the second violin that exceptionally plays soloist lines of the first violin, does not display the lowest Complexity Index values. To disentangle effects of stylistic and structural features of the music *versus* interpersonal dynamics, MSE analysis may be conducted on other music segments where all musician takes an equally musical part (e.g., canonical entries).

Our second hypothesis that the complexity of the leading musician COG sway velocity best correlates with the complexity calculated from the variations of the polygon's area that relate musicians' heads is supported by the results of the correlational analyses: the positive correlation of Musician 1's Complexity Index with the area of the polygon showed that the variations in the behavior of the first violin were strongly associated with those of the group and occurred in the same direction (i.e., as one increased, the other increased, too), while this was not the case of the other musicians, for which the associations were weaker and tended to occur in the opposite direction. This result suggests that the behavior of the leader was the most representative of the behavior of the group.

This study may deliver two social features that account for the establishment of dominance in a group. On one hand, the analysis suggests that the leader is the one that displays the less complex behavior with respect to others. An elaborated joint activity as the one illustrating by a string quartet performance supposes that the relationship between co-performers is regulated as individuals and as a group. In this respect, dominance may be helpful to ensure an effective non-verbal communication in relation to social and musical issues. The leader appears as the one able to "integrate" others' activity and decrease the total entropy of the group. On the other hand, dominance may also be revealed by correlation of the leader's activity and the activity of the group, represented by the variations of the polygon's area. In this sense, even if minimal with respect to the others' activity, dominance may entail a more manifest and continuous effect of the leader on group behavior. These two outcomes are complementary to the results reported in previous studies dealing with the analysis of group meetings: (i) while Hung et al. [10] found that higher activity corresponds to higher dominance, we highlighted that this activity should be characterized by low complexity; (ii) to our knowledge, the correlation between the complexity of the dominant participant with respect to the other group members has not yet been investigated (see [8]).

Future work includes further studies on refinements of models for dominance. Comparison of the results in this paper with the previous results from the analysis of the chronemic component of dominance [19] will be carried out. In addition, our approach will be further developed to improve the continuous analysis of complexity and gain insights on the social dynamics at work. The following two directions are faced: (i) developing a real-time algorithm for MSE, in the Eyesweb platform using both sliding windows and recursive approaches [17], (ii) computing pattern similarity based on fuzzy membership function to ensure the continuity of the entropy measure [2]. These new implementations may lead to the development of automatic models for regulating creative joint activities and supporting the work out of a joint interpretation. Future work is planned within the new EU-ICT FET SIEMPRE project (started on May 2010) to confirm and extend validity of the results presented in this study.

5. ACKNOWLEDGMENTS

This work has been partially supported by the EU-IST Project SIEMPRE. We thank Maurizio Mancini for his precious advice.

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