Multimodal Groups' Analysis for Automated Cohesion Estimation

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ABSTRACT

Groups are getting more and more scholars' attention. With the rise of Social Signal Processing (SSP), many studies based on Social Sciences and Psychology findings focused on detecting and classifying groups' dynamics. Cohesion plays an important role in these groups' dynamics and is one of the most studied emergent states, involving both group motions and goals. This PhD project aims to provide a computational model addressing the multidimensionality of cohesion and capturing its subtle dynamics. It will offer new opportunities to develop applications to enhance interactions among humans as well as among humans and machines.

CCS CONCEPTS

• **Computing methodologies** → *Machine learning*; • **Human-centered computing**;

KEYWORDS

Cohesion; Computational Model; Dataset; Emergent State; Multimodality

1 INTRODUCTION

Groups are getting more and more scholars' attention. With the rise of Social Signal Processing (SSP), many studies based on Social Sciences and Psychology findings focused on detecting and classifying groups' dynamics [21].

Emergent states play an important role in these group dynamics. These are social processes that result from the micro-level affective, behavioral and cognitive interactions among group members, through the micro-processes of group interaction (e.g., [19, 32]). Cohesion is one of the most studied emergent states [38], involving both group emotions [30] and goals [23]. Nevertheless, several definitions and theoretical models of cohesion exist, limiting the comparisons across studies [9, 39]. Over the last decade, scholars focused on how to automatically detect and enhance cohesion but were either relating to a simplistic definition of cohesion or not addressing its subtle nuances and dynamics. Moreover, they suffered from a lack of publicly available data specifically designed for cohesion. The end-goal of this PhD project is to provide a computational model addressing the multidimensionality of cohesion and capturing its dynamics. It will offer new opportunities to develop applications to enhance interactions among humans as well as among humans and machines (e.g. virtual agents and robots).

2 BACKGROUND AND RELATED WORK

2.1 Theoretical models

In the 1940s, Lewin introduced the first definition of cohesion, inspired by the field theory [24]. He referred to it as"*a group characteristic that depends on its size, organization and intimacy*" [25]. Over time, scholars suggested diverse definitions and models to describe this emergent state [2, 12, 28, 43] and the 2-dimensional model introduced by Carron became widely used [8]. More recently, Severt and Estrada [40] proposed an integrative framework, taking into account Carron's model and other researchers' ideas and improvements (i.e., [3, 4, 10, 15]). This framework is structured into two functional properties: the affective one and the instrumental one. The former refers to all the aspects that highlight the emotional impact on a group member and, by extension, the group as a whole (e.g., behaviors or elements of an interaction such as cooperation or exchange). The latter one corresponds to "*those aspects that highlight the goal- and task-based activities of the group*" [40]. Each functional property is separated into two facets (interpersonal and group pride, and social and task, respectively) for which we can distinguish two levels: horizontal and vertical.

2.2 Automated approaches to detect cohesion

Nonverbal communication has been shown to be a more powerful predictor of group-level cohesion than verbal behavior [20]. Among the computational studies interested in predicting cohesion, the ones focusing on small groups' nonverbal cues usually yield better results than the ones focusing on verbal communication. Similarly, studies using a multimodal approach generally obtained better performances compare to the ones using uni-modal models. In a pioneering study, Hung and Gatica-Perez integrated both audio and video non-verbal features, exploring cohesion through multiple dimensions in meetings context [17]. They also collected annotations of cohesion provided by external observers to establish a reference for evaluating their model. Nanninga and colleagues recently extended this work, integrating pairwise and group features related to the alignment of para-linguistic speech behavior [34]. They proved that their audio-based features were more effective at predicting the social dimension of cohesion, with respect to the baseline set in [17]. Both studies defined cohesion prediction as a binary classification problem (i.e., positive or negative). They, however, did not focus on how the task and social dimensions are related to each other. Furthermore, they did not take other phenomena such as leadership or social cognition into account to improve cohesion prediction. With the evidence that cohesion is related to other phenomena [1, 6, 22, 26], integrating features linked to other phenomena in computational models could lead to a better understanding of cohesion and its dynamics. Other studies investigated cohesion at a longitudinal level (e.g., for a period of 20 working days or within a 4-months simulation of a space exploration mission context), with the use of sociometric badges (e.g., [35, 47]). All the features collected through these sociometric badges were, however, only based on individuals and no group level features were collected.

2.3 Cohesion in a virtual environment

Virtual Reality (VR) applications can be used to teach and improve social skills (e.g., [18, 36]), suggesting that interactions in a virtual environment share similarities with the real-world environment. At present, however, only a few studies compared interactions in both VR and real-world settings (e.g., [41, 42]). In [46], Widerström *et al.* designed an experiment consisting of a collaborative puzzle-solving task, carried out by two persons in virtual and real environments to study leadership and performance in the two settings. They found that, in both settings, participants agreed on the leadership and the degree of collaboration, suggesting that the perception of this emergent state is similar in a real and a virtual environment. This study, however, did not focus on the dynamics of these phenomena and only explored dyadic interactions. To the best of my knowledge, there is no research designed for studying cohesion, at a group level, that includes both virtual and real-world settings. Such study would help to gain insight on how cohesion emerges and varies in a virtual environment with respect to a real-world environment.

3 RESEARCH QUESTIONS

This PhD project is aimed at building a computational model able to predict the dynamics of cohesion and to capture the relationships between its social and task dimensions. My research will specifically focus on the social and task dimensions at the horizontal level, based on Severt and Estrada's framework [40] as it aligns with the dominant approach in the current teams' literature (e.g., [1, 6, 22]). Furthermore, no automated study of cohesion was ever based on this framework, even though it provides a finer level of categorization than other models (e.g., Carron's model [8]). It also acknowledges and integrates that cohesion is a dynamic phenomenon that can be expressed in various ways depending on the context. To achieve the goal of this PhD project, the focus will be laid on the following research questions:

RQ1: *Which multimodal socio-behavioral features are relevant to predict cohesion and the relationships between social and task dimensions? How these features can be coded to feed a computational model?*
Intuitively, we could expect that both social and task dimensions are expressed differently, through various modalities, as they serve distinct purposes (quantifying social bonds and quantifying task commitment, respectively). Psychological models (e.g., [8, 40]), however, assume that theses dimensions are not orthogonal, meaning that there may be behavioral correlates which are indicative for both dimensions. Previous approaches do not take into account these relationships. The context in which the group is interacting also plays an important role in the group cohesion. Past research, however, mainly focused on a meeting scenario where, for example, full-body movements are restricted. Moreover, no innate group features have been developed. Features are either based on dyadic or individual features that are then aggregated to form a group feature. As the goal is to detect the dynamics of cohesion at a group level, it is important to develop a set of group and individual multimodal features shared by both dimensions.

RQ2: *How the knowledge on other cognitive and behavioral phenomena can be explicitly modeled to structure a computational model of cohesion?*
To the best of my knowledge, no study interested in automatically predicting cohesion has integrated any other cognitive or behavioral phenomena (e.g., motivation, leadership, performance, emotions, social cognition) in their model. As stated in Severt and Estrada's study, various links and relationships between cohesion and other phenomena may be observed depending on the function (e.g., instrumental), the facet (e.g., social) or the level of analysis of cohesion (e.g., horizontal) that is being investigated. With this in mind, the focus will be on integrating the leadership and social cognition phenomena into the computational model's architecture. The cohesion-leadership link has already been proved (e.g., [27]) and would give more insights on the interaction while warmth and competence (i.e., social cognition) could help to give some extra contextual information regarding the group's members perceptions.

RQ3: *What computational architectures can be envisaged to predict cohesion and its dynamics?*
Most of the computational studies related to cohesion rely on different definitions, making it difficult to compare findings across studies. Moreover, these studies developed Machine Learning models to predict the presence or the absence of cohesion for the social and task dimensions, separately, without investigating the relationships between cohesion's dimensions over time as well as with other group phenomena. It highlights the need to develop a comprehensive computational model to address these comments.

RQ4: *How does virtual cohesion could improve collaboration in multimodal systems?*
New paradigms of group interaction could emerge with the advent of new technologies and the actual world context (e.g., health crisis, climate change) as more and more tools are developed to encourage people to meet and gather virtually (e.g. ICMI2020 as a virtual conference). Understanding how cohesion manifests in both virtual and real environments would provide another angle of research and enrich our comprehension of cohesion, leading to the development of more robust multimodal systems.

4 RESEARCH PLAN AND METHODOLOGY

This research is conducted in four stages within three years, with the following proposed scope, methodology, and time frames.

Stage 1: Investigating the foundations of cohesion
Understanding the concept of cohesion and being aware of the different methods used to assess it (e.g., questionnaires or coding schemes) is a key part of the project as scientific knowledge from Social Science and Psychology will drive and inform research on

the computational model. The first months of the project were dedicated to (1) conduct a comprehensive literature review on cohesion covering both Psychology and Computer Science approaches, (2) choose the most suitable multidimensional theoretical model of cohesion that acknowledge relationships between its dimensions and with other phenomena and (3) choose a well-established questionnaire that can assess and measure various dimensions of cohesion. As a result of these investigations, my PhD project will focus on the instrumental property of cohesion at a horizontal level based on Severt and Estrada's model of cohesion [40]. This model integrates the most accepted ideas from the Psychological literature on cohesion and acknowledges the multidimensionality of cohesion. It also suggests that some relationships exist between its dimensions and with other phenomena, highlighting the need for exploring their impact on cohesion. The GEQ questionnaire [8] will be used to measure self-assessments of group cohesion (i.e., its social and task dimensions). This questionnaire is widely used and several studies have shown how the GEQ can be leveraged for addressing group situations in different contexts (e.g., [7, 11, 16, 33]).

Stage 2: Collecting a multimodal dataset for cohesion and group analysis
The second stage, which consisted of designing and performing a data collection to capture the dynamics of cohesion, ran throughout the end of the first year. It also included multiple rounds of pre-tests, the recruitment of the participants and the post-processing of the data. The data collection involved six other researchers from four different laboratories (see [31] for more details). We focused our efforts on capturing the variations of cohesion (i.e., increase or decrease), in the context of an escape game (i.e., a social game). Social games have been considered as a viable research methodology to address the subtle nuances of human-human communication by several research domains (e.g., [5, 14, 37, 44]). This stage aimed to collect the first multimodal dataset (containing audio, video and MoCap data) specifically designed for the study of cohesion dynamics. Besides, we also gathered self-assessments of cohesion, participants' emotional state and perceived leadership and warmth and competence through the use of well-established questionnaires.

Stage 3: Building a computational model
This stage aims at designing the model in such a way that it will: (1) follow theoretical sociological models, (2) integrate the multidimensional nature of cohesion, (3) take the temporality and the relationships between its dimensions over time into account and (4) consider the impact of other phenomena on cohesion.
In order to address these goals, the first step consists of defining a set of multimodal nonverbal features that will feed the computational model. The challenge is to define a common set of features that will be used to detect changes in the dynamics as well as some dimension-specific features that would help to refine the prediction for each dimension in order to reflect the fact that social and task dimensions are not orthogonal. Afterwards, how to capture the dynamics of cohesion should be addressed. As a first approximation, the focus will be to address such dynamics as an increase or decrease of cohesion. This problem can be tackled as a binary classification task (e.g., Increase/Decrease) or a multiclass classification task (e.g., Increase/Stable/Decrease). A more refined step will consist of addressing dynamics as a regression task (e.g., by how much the cohesion varied). At this point, we could imagine running several Machine Learning models in parallel, or sequentially, to independently predict each dimension. Another option would be to design a multiclass model to predict both dimensions at the same time. Finally, the features related to the other phenomena could be used at multiple layers: as part of the feature layer (input) and/or as part of a "context" layer that would come on top of the feature layer to augment the input features by using additional information extracted from these phenomena.

Stage 4: Evaluating the computational model
The evaluation of the computational model will be performed by comparing the output of the model with the annotations provided by the participants and by external raters. These two kinds of annotations will be used in order to yield a "*true*" assessment of cohesion by minimizing the known biases introduced by self-assessment (e.g., drifting off the ratings towards socially desirable characteristics) and external assessment (e.g., problems in the attribution of characteristics) [45]. The two last stages are expected to be iterative over the last two years of the PhD program. The features will first be computed and then incrementally adjusted. We will have a similar approach for the overall architecture of the computational model and its implementation as the plan is to integrate various novelties.

5 RESULTS AND CONTRIBUTIONS TO DATE

5.1 Collection of the GAME-ON dataset

GAME-ON is composed of five tasks designed to elicit variations (i.e., increase or decrease) of the social and task dimensions of cohesion, following Severt and Estrada's framework of cohesion [40]. The GEQ questionnaire [8] was administered after each task in order to observe variations of cohesion all along with the data collection. More than 11 hours of multimodal data have been recorded. After post-processing, GAME-ON [31] now contains data of 15 groups of three participants without any interruption or missing data. Figure 1 shows three participants posing and their corresponding 17-points skeleton obtained with the MoCap system.
Statistical analysis, including Friedman tests and post-hoc Conover's tests with a Bonferroni correction, has been conducted based on the cohesion scores. These scores are computed per participant and per dimension (i.e., social and task) from the six self-assessments collected. The analysis confirmed that we successfully managed to control the variations of cohesion in the expected directions (increase or decrease) for the social dimension and four transitions over five regarding the task dimension.

5.2 Ongoing studies

The two first stages are now completed and a first exploration of the data led to the following ongoing studies:

Setting up a baseline for predicting decreases of cohesion using MoCap-based features and self-assessments of cohesion and assessing features impact and importance on the model.
First, a set of 14 group features and their respective mean, standard deviation, max, min and skewness, were computed. They are either calculated at an individual level and then aggregated or computed

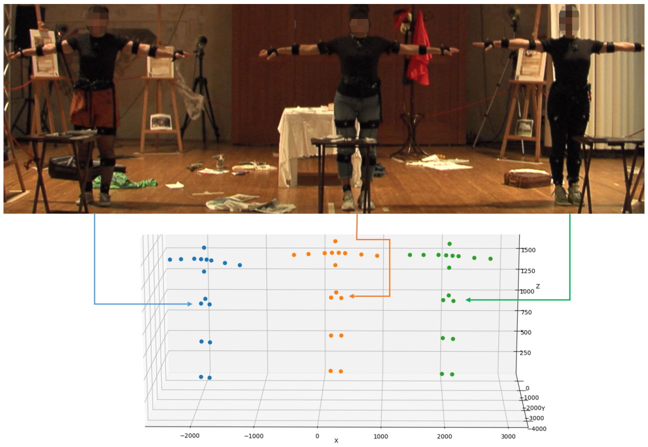

Figure 1: Example taken from the GAME-ON dataset showing a group posing during the data collection and the three corresponding 17-points skeletons.

at a group level (see Table 1). Then, we produced the labels (increase or decrease) by taking the mean rank difference between two consecutive GEQ scores. With a multilabel setting and using a Random Forest classifier, we reached 64% ± 3% and 67% ± 3% classification accuracy and 64% ± 3% and 67% ± 3% F1-scores for task and social dimensions, respectively. We employed a repeated nested 10-fold cross-validation with five repetitions across all slices to validate our model. Cross-folds were randomly generated and stratified over the set of groups and tasks. The number of pruned decision trees and their maximum depth were estimated using grid search on a 5-fold cross-validation. The best model was selected using the highest average accuracy over both social and task dimension and used pruned decision trees with a maximum depth of 5, a total of 100 estimators, and *Gini imbalance* evaluation criterion. Finally, we provided a method based on notions from cooperative game theory (i.e., SHAP values [29]) to assess the feature set impact and importance on our setting.

Table 1: Description of the aggregated and innate nonverbal group features used to predict decreases of cohesion.

Aggregated group features	Innate group features
Max distance between group members	Facing balance
Spacial association of max distance	Participation equality
Amount of hand gestures while not walking	Turn-taking freedom
Average amount of walking	Number of floor exchanges
Average posture expansion	Presence of F-Formation
Posture difference in group	
Time touch is detected	
Time someone is being faced	
Movement difference in group	

Exploring the cohesion-social cognition relationships.
In addition to participants' self-assessment of cohesion, GAME-ON also comprises both self and external assessments of the two major dimensions of social cognition: Warmth and Competence (W&C) [13]. The first phase consisted of exploring what were the correlations between the GEQ and the W&C questionnaires. The next step is now to develop multimodal features related to W&C, based on the previous analysis and psychological findings (e.g., kinetic energy and amplitude of arm movements for W&C, respectively). Then, we should ensure that these features are correlated to the W&C questionnaire. Finally, observing their correlations with the GEQ questionnaire would strengthen the link between these phenomena.

6 FUTURE WORK AND CONTRIBUTIONS

As part of the iterative process presented in stage 3 of Section 4, the baseline for detecting changes in the dynamics of cohesion will continue to be improved by integrating other multimodal features (with a focus on audio and video modalities). A particular effort will be made in order to design the computational model's architecture so that it will integrate the relationships between the social and task dimensions as well as with the other phenomena. As part of the last stage of Section 4, an external annotation campaign will be run. The goal is to see if there is an agreement between self and external ratings in order to study how to combine them to limit or avoid the biases introduced in each type of label. Finally, a pilot study will be designed to compare cohesion in both real and virtual environments. In addition to the existing contributions previously mentioned, the following major contributions are envisioned:

(1) Advancing our understanding of cohesion by providing a set of features able to capture the dynamics of cohesion that are shared between social and task dimensions of cohesion.
(2) Providing a computational model able to capture the relationship between social and task dimensions of cohesion and to predict the dynamics of cohesion.
(3) Running a pilot study to compare cohesion in both real and virtual environments.

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