Memory Effect in Expressed Emotions During Long Term Group Interactions

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Abstract. Long-term interactions in groups can be monitored through games in which the participants need to show their social preferences by making choice to help or to use egoistic game strategy. In this paper we analyse the facial expressions of a group of isolated individuals (astronauts) during repeated interactions in subsequent encounters in a game. The astronauts were taking part in the Mars-500 isolation experiment and their relations were influenced by the everyday interaction in this untypical environment, and monitored through the cooperative game. We analysed different statistical properties of the recorded emotional facial expressions of the astronauts, where emotions were determined by the FaceReader software. We found that there is a memory effect between the collective emotional expressions corresponding to subsequent experiments, separated by two weeks time period. This dependance suggest that it is possible to predict the development of interpersonal relations in groups of isolated individuals. In a broader perspective, this finding can inform the design of long-term interaction behavior of artificial agents.

1 Introduction

Measuring and analyzing the emotional states in long-term interactions is important for groups of individuals that need to engage in such interactions and especially if these interactions are in confined and isolated environments, such as submarines, arctic expeditions, and space ships. Healthy emotional states are as important for the success of the long-term missions and influence the interpersonal relations in the group.

The topic of measuring emotional behavior and interactions trough games gains an increasing interest [3,13,15]. Games provide semi-structured context for interaction between humans or between humans and agents. This is one among several reasons for using games as interaction medium between humans and agents [2,4,5,15]. In addition, the use of games can increase the entertainment quality of the interaction, and can help to reveal relationships that are hidden in different contexts or even relationships that are subconscious.

The computer games could be a tool for measuring and establishing long-term relations since they may include many different aspects of real life interactions between people. In this case they can be used to understand and teach the

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rules of collaboration and even create artificial agents that can function as a collaboration partner [2,15]. Many game designers are currently exploring the added value of cooperative strategies within their games [8] such as reaching a goal with limited resources. Gorbunov et al. [14,15] redesigned and tested a game which utilizes on collaborative patterns to induce cooperation within the game. The game was designed to be played multiple times - each time a player would choose to help or ask for a help expecting that next game the chosen partner may help back or request a help.

In this paper we show the analysis of the longitudinal game interactions through data from the Mars-500 isolation experiment. During this experiment six participants have been isolated for 520 days to simulate a flight to Mars. Every other week the participants played the game that was specially adapted from the existing Collored Trails game that is used in game theory and experimental economics to study cooperation and fairness. During the game sessions the crew members interacted with each other through a computer-based environment. To monitor emotional states in the group we use video records capturing facial expressions of the crew members during the game play. In this way, correlations between the events that occurred during game play and the coinciding facial expressions can be made. We need to mention that in this work we do not focus on the problem of facial expressions recognition. Instead, we utilize the progress in this field made by other researchers and companies by using commercially available software that can quantify facial expressions with good accuracy. This allows us to shift the focus from the problem of facial expressions recognition to the problem of interpretation of the time dependent facial expressions in a way that is relevant in the context of interpersonal relations and long-term effects of isolation. We discuss the general properties of the recorded data and the software that we used to automatically generate data describing the facial expressions of the participants. The main contribution of the paper is that we found memory effect observed for the collective emotional states, as revealed by the facial expressions, for the neighboring experiments separated by two weeks.

2 Background

2.1 Board Games for Long-Term Interaction

Several games have been used for monitoring and analysing collaborative behaviors of players. One example is Colored Trail game that has been designed to enable analyzing of the decision making strategies of multiple players in varying settings and complexity [16]. Different variations of the game have been used to study human-human and human-agent interactions [1,10–14,16–19,22,23]. The Colored Trail game resembles real life situations in which people have different goals and need some resources to reach these goals i.e., the resources can have different values to different players. A redistribution of the resources can be done if the players exchange resources (chips) so one or more players can came closer to the goal. If a player helped other player without having a benefit (because with any combination he/she would not have won this time) he can expect that in the next game the helped player will return the favor. Therefore, the game is interesting for analyzing long-term relationships since it contains both competitive and collaborative (social) components.

More specifically, the game is played on a rectangular board composed of colored squares (see Fig. 1).

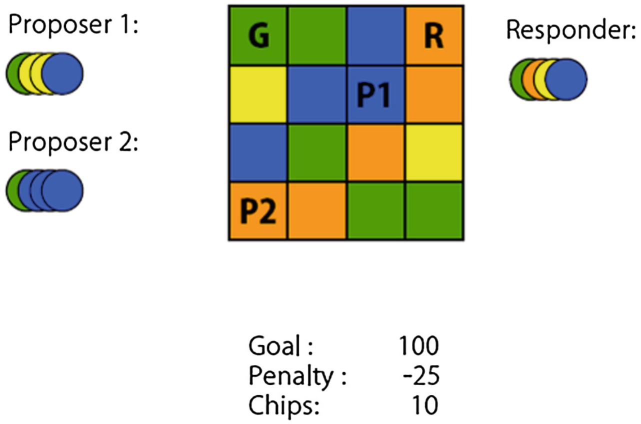

Fig. 1. Example of the colored trails game on the response phase. (Color figure online)

In the beginning of the game every player is placed on one of the colored squares of the board. Additionally to that one square is assigned to be the goal that should be reached by each player. Every player receives a set of colored chips which represent the resources of a player. The colors of the chips are taken from the same set as the colors of the board squares. Players can move on the board using their chips - a chip with a certain color will make possible one move to a neighbouring square with the corresponding to the chip color. The moves are restricted to horizontal or vertical moves to one of the neighboring squares. By making a step on the board a player irreversibly spends a chip. The goal of the player is to move as close as possible to the goal-square, spending a minimum of chips. Before making their moves players are allowed to exchange some of their chips with another player. Any exchange of chips is possible if both participants of the exchange agree to do this exchange. This redesigned version of the Colored Trails game is a redesign of the initial game that was proposed in Harvard university by Gal and colleagues [13] and is used in the game theory and experimental economics to study cooperation and fairness.

3 Analyzing Emotional States Caused by Interpersonal Relations

We assume that by measuring and analyzing emotional states of the group members caused by the natural development of their interpersonal relations and their emotional states are very tightly bound and influence each other. Healthy emotional states are as important for the success of the long-term missions as the interpersonal relations in the group. To monitor emotional states in the group we use video records capturing facial expressions of the crew members during the game play. In this way, correlations between the events that occurred during game play and the coinciding facial expressions can be made. We need to mention that in this work we do not focus on the problem of facial expression recognition. Instead, we utilize the progress in this field made by other researchers and companies by using commercially available software that can quantify facial expressions with good accuracy. This allows us to shift the focus from the problem of facial expressions recognition to the problem of interpretation of the time dependent facial expressions in a way that is relevant in the context of interpersonal relations and long-term effects of isolation.

3.1 Video Records from Mars-500

The video records of facial expressions were collected during the Mars-500 isolation experiment in which six participants were isolated for 520 days to simulate a flight to Mars. Every second week the participants had to interact with each other through a computer environment for approximately 30 min as a part of this experiment. During these sessions the participants were sitting in front of the computers performing different learning tasks supplied by the MECA software [20] and playing the CT game [16] with each other. The frontal video records of facial expressions were made by the cameras located on the participants' computers. To monitor emotional states in the group we applied correlation analysis between the events that occurred during game play and the coinciding facial expressions.

3.2 Face Reader

To extract facial expressions from the available video records we have used the FaceReader commercial software developed by VicarVision and Noldus Information Technology [6]. The FaceReader software can recognize facial expressions by distinguishing six basic emotions (plus neutral) with accuracy of 89% [6]. In particular, FaceReader recognizes happy, sad, angry, surprised, scared, disgusted and neutral components of the facial expressions. The system is built to correspond to Ekman and Friesen's theory of the Facial Action Coding System (FACS), that states that basic emotions correspond with facial models [7]. For an overview of the progress in the field of automatic facial expressions recognition see [9,21]. In the current study we have used FaceReader to generate components of the facial expression for every third frame of the video. It gives the time separations between the two neighboring data points (components of the facial expression) equal to 120 ms. By considering only every third frame we could reduce the computational time needed for the generation of the data describing facial expressions in a quantitative way, and the computational time required for the analysis of these data. By the chosen frame rate we still were able to get smooth dependencies describing the facial expressions.

3.3 Classification of Statistical Properties of the Data

The data generated by the FaceReader software can be considered as a set of real numbers depending on four variables: $v\,(c, u, e, f)$, where c indicates the component of the facial expression, u is used to indicate the participant, e is the index of the experiment and f is the frame index. The type of the facial expression can have one of the following seven values: "neutral", "happy", "sad", "angry", "surprised", "scared" and "disgusted". In our data from the Mars-500 experiment, the second argument (u) can have six different values, since we have six participants in this experiment. The third argument (e) is the index of the experimental session. Since we had 33 experiments, the index runs from one to 33. The separation between every experiment was two weeks except for experiments 18 and 19, which were separated by four weeks because of the simulation of a landing on Mars during which it was not possible for the crew members to play the game. The last argument (f) is the index of the frame in the given video.

The arguments present in the data can be classified based on their properties. First we distinguish between homogeneous and inhomogeneous variables. By homogeneous variables we understand those over which averaging makes sense. In our case all variables except the type of the facial expressions are homogeneous. It means that we can average facial expressions over users, for example, to calculate the average happiness of the crew. We can also average the facial expressions over different experiments to find how the happiness of a given user changes depending on the duration of the experiment. It is also possible to average a given component of the facial expressions over the frames of the video to find the average happiness of the given user in the given experiment. In contrast, we cannot average happiness and sadness because these properties have different meanings. However, the different components of the facial expressions can be combined in a way that is more sophisticated than averaging. For example, we could combine different components of the facial expressions in a way done by principal component analysis or independent component analysis, which could be helpful for identification of the most important or independent features. The variables can also be classified depending on whether they are subsequent or not. By subsequent variables we understand those variables for which a natural ordering of values exists. In the considered case the two variables, frame index and experiment index, are subsequent. These indexes can be ordered chronologically. In contrast, there is no preferred ordering of the components of the facial expressions and the users. We can group different values of a component of a facial expression if these values correspond to different values of a given homogeneous variable and to the same values of other variables. This procedure can be applied to several homogeneous variables at the same time. In this way we can get seven different properties. We will denote these measures by the removal of the arguments that were used for the grouping. Specifically, we get the following measures:

$$v\,(c,e,f) = \sum_{u} v\,(c,u,e,f)\,, \tag{1}$$

$$v\,(c,u,f) = \sum_{e} v\,(c,u,e,f)\,, \tag{2}$$

$$v\,(c,u,e) = \sum_{f} v\,(c,u,e,f)\,, \tag{3}$$

$$v\,(c,u) = \sum_{e}\sum_{f} v\,(c,u,e,f)\,, \tag{4}$$

$$v\,(c,e) = \sum_{u}\sum_{f} v\,(c,u,e,f)\,, \tag{5}$$

$$v\,(c,f) = \sum_{u}\sum_{e} v\,(c,u,e,f)\,, \tag{6}$$

$$v\,(c) = \sum_{u}\sum_{e}\sum_{f} v\,(c,u,e,f)\,. \tag{7}$$

3.4 Averaging over Experiments

Averaging over users and experiments, i.e. the first two properties did not result in significant dependencies. We will give the results of averaging over the subsequent experiments, the third property ($v\,(c,u,e)$), since it relates to the memory effects. This property removes the dependency on the time frame, since we average over different frames from the same experiment. As a result we get different components of the facial expressions of different users as functions of the experiment index. These properties can be of particular interest since they potentially could capture a long-term effect of the isolation. For example, we could expect that the facial expressions of given users become more (or less) happy the more time they spent in isolation.

As an illustration, in Fig. 2 we show the dependence of three different components of the facial expressions (neutral, happy and sad) as functions of the experiment calculated for the one of the users.

With the black histograms we show the number of the available data points, divided by 10^5, as a function of the experiment number.

In Fig. 2 we cannot see any obvious dependence on the experiment number. However, we can see that some components of the facial expressions systematically increased for five experiments in a row. Since it is not obvious if there is some regularity in the considered dependencies, we have performed a quantitative estimation of this regularity. In particular, if a vector depends on a parameter, the distance between a pair of vectors decreases on average, if we decrease the difference between the pair of parameters corresponding to the two considered vectors. Therefore, we can use the average distance between the neighboring vectors as a measure of the regularity of the dependency of the vectors on a parameter. In our case the vector is composed of seven average components of the facial expressions and the parameter is the integer index of the experiment. To measure the similarity between a pair of seven dimensional

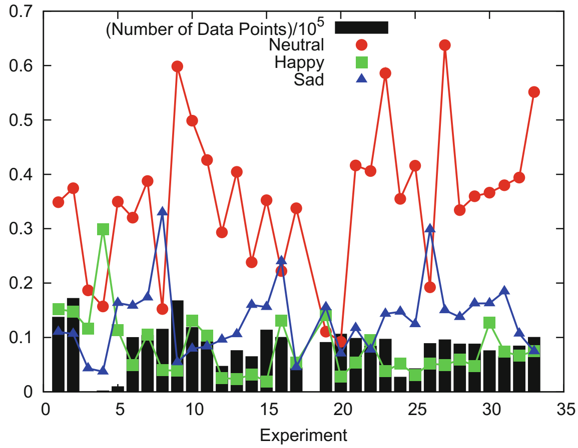

Fig. 2. Three different components of the facial expressions of an user through the evolution of the experiment

(7D) vectors we used the Euclidean distance. The average distance between the average values of the facial expressions corresponding to all available neighboring (subsequent) experiments has been calculated for all six users. Then we generated a new sequence of the 7D vectors just by shuffling the original sequence. If there was some dependence of the vectors on the experiments it was destroyed by shuffling. For the new sequence of the 7D vectors (average facial expressions) we have also calculated the distance between the neighboring vectors. This procedure has been repeated 10^4 times to determine in what percentage of cases the average distance between the neighboring vectors can be as small as, or even smaller than those calculated for the original ordering of the vectors.

This procedure has been performed for all six users and the following percentages have been found: 2.5%, 85.4%, 5.2%, 9.7%, 43.7% and 42.4%. These results indicate that the used measure of regularity calculated for the dependencies shown in Fig. 2 is very close to the values of the measure of regularity calculated for irregular sequences of vectors. Based on that, we can conclude that we have no solid reason to think that we are able to see some regular dependence of the average facial expressions on the experiments.

4 Dependency on Users

The fourth property ($v\,(c, u)$) removes the dependency on experiment and frame index. In other words, we get a property that depends only on the type of the component of the facial expressions and the user. In this way we can determine how happy or sad or angry a given group member was on average during the long-term isolation. This property can be used to characterize the person and his/her reaction in isolation. However, to study effect of isolation on the emotional state (facial expressions) we need to have video records for non-isolation conditions.

As a result of the considered averaging over the frames and experiments we get $6 \cdot 7 = 42$ values. These values are shown in Fig. 3.

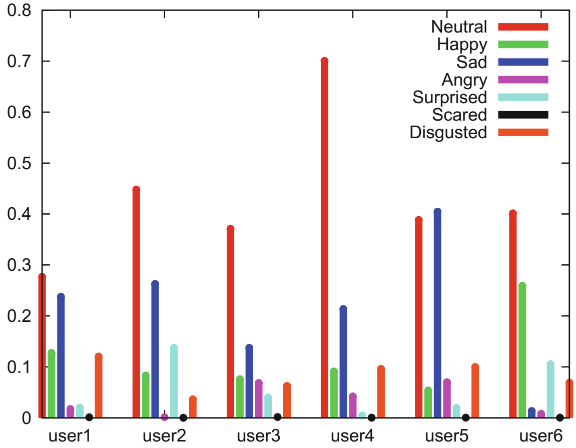

Fig. 3. Average values of seven different components of the facial expressions given for six participants of the Mars-500 experiment

4.1 Dependency on Subsequent Experiments

The fifth property ($v(c, e)$) is obtained by averaging over users and time frames. This property gives the combined emotional state of the crew as a function of the experiment index. For example, with this property we could see how the average happiness of the crew depends on the time (number of weeks) spent in isolation. This property is shown in Fig. 4. This figure is very similar to Fig. 2. The difference between Figs. 2 and 4 is that Fig. 4 shows the values averaged over all six users and Fig. 2 only shows values corresponding to user3. Moreover, in Fig. 4 we also show the "disgusted" component of the facial expression as a function of the experiment index. Like in the case of the separate consideration of the users we have performed a numerical estimation of the regularity of the dependency. For that we used the average distance between the neighboring vectors as a measure of the regularity. As a result we found that, after averaging over the users, the difference between the averaged facial expressions from neighboring experiments is, on average, smaller than the difference between the averaged facial expressions taken from two randomly chosen experiments. The probability that the difference between the neighboring experiments, in terms of the average facial expression, can be as small as it is, or even smaller, is equal to $8 \cdot 10^{-4}$. From this result we can conclude with high confidence that there is a relation (similarity) between the emotional states of the crew corresponding to the experiments separated by two-week time intervals. As a consequence, the averaged emotional state of the crew in a current experiment can be used as a predictor of the average emotional state that will be observed in two weeks. The sixth and seventh property did not show significant results.

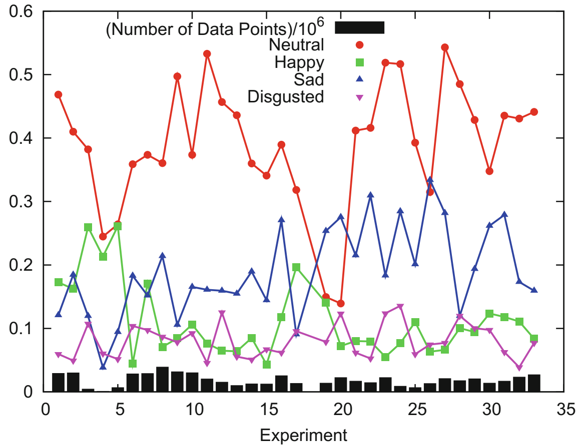

Fig. 4. Averaged (over frames and users) components of the facial expressions as functions of the experiment index

5 Discussion

In this paper we have proposed measures that can be used for analysis of the data generated by facial expressions recognition software in groups of people who are involved in interactions that can provoke emotional reactions. We used repeated cooperative (economic) games for monitoring the groups behavior, but also for provoking emotional reactions in the players. Fe proposed measures to find dependencies in the obtained data. Based on these measures we have found a statistically significant correlation between the average emotional states from two neighboring experiments separated by two weeks. This result means that there is a memory in the dynamics of the average emotional state of the crew so that two weeks cannot completely destroy the memory about the previous emotional state. This property of the dynamics of emotional states can potentially be used to predict emotional states of the group for the next few weeks.

The proposed method can be used for monitoring and predicting of the emotional state of group of isolated individuals. The method can also be used to design social agents. Previous findings of this research have been used for the design of social agents [14]. These agents were shown to outperform agents that do not utilize on the social behavioral strategy proposed in [14]. These design principles can be exploit for design of social strategies for long-term interactions between humans and virtual agents and in human-robot interaction.

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