Monitoring Emotions and Cooperative Behavior

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Monitoring Emotions and Cooperative Behavior

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1. INTRODUCTION

1.1 Motivation

There are many long-term missions that are performed by small crews in isolation. Examples of these types of missions are those performed on the international space station, polar research stations, submarines, oil platforms and meteorological stations. The success of such missions strongly depends on the emotional states of, and the interpersonal relationships between, the crew members. Crew members' emotional problems or conflicts in a crew can lead to mission failure. For instance, intra-crew tension can cause formation of subgroups, disruption of cohesion, scapegoating, and refusal of communication and collaboration. The issue of the psychosocial health of crew members also is very important because long-term isolated missions are usually performed in extreme physical conditions (such as weightlessness, low or high temperatures, radiation, or poor lighting), that often have a strong and negative influence on the psychosocial atmosphere in the team. Moreover, these missions are affected by negative psychological factors such as the isolation itself, spatial and social confinement, and risks. In this context it is very important to develop methods for monitoring and improving the psychosocial atmosphere in isolated goal-oriented teams.

The direct way to collect data about emotional states of crew members and the interpersonal relationships between them is to complete standardized questionnaires. The advantage of this method is that people are inherently good at detecting emotions of others and at understanding interpersonal relationships between each other. The disadvantage of questionnaires is that people can be biased and/or dishonest, especially if they need to reveal their feelings and their perspective of the conflicts in which they are involved. Moreover, repeated answering of extensive questionnaires can be very boring and, as a consequence, the crew members may either refuse to complete the questionnaires or they will provide low quality input.

Another promising approach to access emotions of the team members is to observe their non-verbal behavior or their physiological signals. The most popular inputs for measuring emotions are: voice intonation [56, 47], body movements [5, 39], facial expression recognitions [63, 41, 69, 44, 54], and physiological signals [65, 28]. The fact that people express their emotions naturally through facial expressions and voice intonation makes monitoring of these signals very promising. There are several advantages of monitoring of non-verbal behavior and physiological signals, as compared to the questionnaires approach: (1) it does not require direct involvement of the crew members and can be done automatically, (2) it provides an objective input and (3) it can capture some aspects of emotional states that are missed by crew members themselves.

In addition to the tools for an automatic measuring of emotions, it is important to have tools for measuring interpersonal relationships. Interpersonal relationships are naturally expressed through interactions between people. In this context the use of computer games is very promising because games provide a way to formalize and simplify interactions between people. Computer games give researchers a mechanism to control and restrict the way in which people can interact with each other. In this way the researchers can focus on those aspects of interpersonal relations which are of particular interest for the research. Moreover, games provide a control over the complexity of the interactions which is important for keeping a balance between the richness of the interactions and the simplicity of the analysis.

1.2 Structure of the Thesis

In this work we study a possibility to measure social preferences of crew members through their interaction in a computer game. Our primary focus is on aspects of interpersonal relations such as fairness and cooperation. To accomplish this focus we have proposed a special class of games for which the decisions of the players in the game can be easily bound to the social preferences of the players. This method is based on the use of payoff spaces with a special structure that creates a dilemma between different social preferences. We have also proposed a parameter that indicates if an action in the game was fair or cooperative, sacrificing or exploiting. This measure used for the description of a single action, by itself, has been used to define two cooperation ratios that describe a set of actions made by a player. The two cooperation ratios can be used to describe how cooperative a player was and how symmetric his/her cooperative behavior (exploiting or sacrificing) was. We have also demonstrated that the difference between the players in terms of the two cooperation ratios is statistically significant. The cooperation ratios provide a descriptive approach to the data.

To have a model with an explanatory power we have introduced a utility function describing the social preferences of the players. In the utility based approach, decisions of a given player in bilateral interactions can be described by three utility parameters. These utility parameters can be used to estimate the values of the cooperation ratios associated with a given player. As a consequence, the utility based approach can be considered as a more detailed model of gaming behavior as compared to the approach utilizing the cooperation ratios. Moreover, the utility model can explain, to a certain extent, why a given player made a given decision in a given game while the cooperation ratios only give the populations of different types of decisions in an empirical way. In other words, we can say that the model based on cooperation ratios has only descriptive power while the utility based model has an explanatory power.

To bind the utility model with the real decisions of the player in a meaningful way we have developed a model that captures the possibility that a player may have limited cognitive capabilities to see all possible solutions and, therefore, can make mistakes. In particular, we have introduced three sources of combinatorial complexity in the game, as well as numerical measures of them, and have demonstrated that these measures have a statistically significant correlation with the probability of the game options to be noticed by the players. In addition, we have proposed two simple and one generalized probabilistic models of noticing options in the game. We have shown that the use of these models can significantly improve the agreement between the utility based approach and the approach based on the use of cooperation ratios. We have demonstrated that probabilistic models of noticing are important components in deriving the utility parameters (social preferences) of players from a sequence of their decisions. In addition, the parameters of the models of noticing can potentially be useful as measures of cognitive abilities and indicators of cognitive fatigue, which is important in the context of an automatic monitoring of the psychosocial state of a crew.

The above described approach has been used to analyze decisions of the players in the first phase of the game in which they need to propose an exchange of resources to their opponents in the game (the proposition phase). To describe the second phase of the game, in which players decide if they want to accept or reject proposals of other players (the response phase), we introduce alternative models. The first of the models used for the analysis in the response phase of the game is a simple linear model that assumes that responders combine their own benefit and the benefit of other players in a linear way. We demonstrate how this model can be parameterized based on the decisions of the responders. Additionally, we define 12 classes of responses and visualize social preferences of the responders as a network of preferences over the introduced classes. We further demonstrate how a network of preferences can be used to calculate numerical measures of the preferences over different kinds of decisions. To quantify the preferences over different kinds of responses we use Page rank algorithm and Elo's indices. We also show how these measures can be combined with each other to calculate some analogues of the cooperation ratios introduced for the proposition phase of the game. Finally, we demonstrate that cooperation ratios calculated for the two different phases of the game have a statistically significant correlation that, by itself, provides a strong proof that the values of the introduced cooperation ratios are meaningful.

In the second part of the thesis we focus on the analysis of the video records of the facial expressions made during the Mars-500 experiment (described further in paragraph 1.4 below). To extract numerical values describing facial expressions of the participants in an automatic way we use commercially available software (FaceReader from Noldus Information Technology). We propose a simple classification of different statistical properties that can be calculated based on the numerical data generated by the FaceReader software. We discuss in detail the meaning of the defined properties and present two positive results. First, we found that there is a memory effect between the collective emotional states of the crew, as seen in the facial expressions, corresponding to neighboring experiments, separated by a two weeks time period. Second, we demonstrate that there are statistically significant relations of different types (positive and negative) between the facial expressions of different crew members. We demonstrate how this relation can be found, visualized and interpreted. We also discuss how the strengths and types of these relations can potentially be used to quantify emotional bindings between different crew members. In addition to the calculation of the basic statistical properties of the facial expressions we develop a mathematical model that can explain the observed facial expressions in terms of the events of different intensities and types. In more detail, the presented model assumes that a current facial expression can be represented as a mathematical function of the following three arguments: (1) the intensity and type of the event, (2) time separation between now and the moment when the event happened and (3) the facial expression at the moment of the event. First, we make an initial guess about the structure of this relation. Then we use this guess as a starting point in a genetic search of a better function. Finally, we perform an additional optimization of the parameters of the function found in the genetic search. We demonstrate that both, genetic search and optimization of the parameters, improve the accuracy of the model. This part of the work is just a proof of concepts demonstrating a possibility to find a mathematical model that could explain the observed expressions in terms of the emotions that are expressed. In other words, such a model could be used to generate a sequence of emotions (their intensities, types and location on the time scales), based on the observed sequence of the facial expressions.

1.3 Social Dilemmas in Simple Games

Game theory provides a model of interaction between different decision makers. Within this model, the outcome of the game is summarized by payoffs allocated to each player. The payoff that a given player receives is assumed to depend on choices made by the considered player and on choices made by other participants.

In this section we provide an overview of one of the simplest class of games in which only two players are involved and every player has only two choices. Moreover, we consider symmetric games in which payoffs of two interacting players depend on their actions and the actions of their opponents in the same way. In this section we use this class of simple games (symmetric bilateral two-choices games) to introduce the concept of the social dilemma. We show that the considered class of the simple games provides four qualitatively different games (social dilemmas). Among these four games we have the prisoner's dilemma that will be used later in combination with the Ultimatum Game to introduce a more complex game (Colored Trails), which we use in our study as a tool for measuring cooperative behavior and social preferences.

The payoffs in a symmetric game are given by the payoff matrix shown in table 1.1. The rows and columns of the table correspond to the two actions

	A	B
1	w, w	x, y
2	y, x	z, z

Tab. 1.1: Payoff matrix of a symmetric two options game

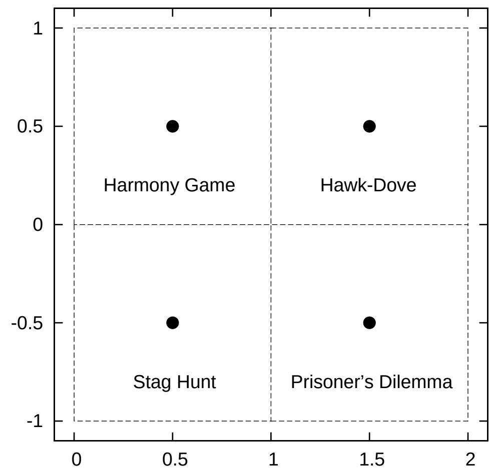

Fig. 1.1: Four regions corresponding to four different games

available to the first and the second players, respectively. The first and the second numbers in the cells are payoffs of the first and second players, respectively. We do not change the logic of a game if we multiply all the payoffs by the same positive number. The logic of the game is also invariant with respect to a constant shift of all payoffs. We also can change the numeration of the actions. Using these three properties we can always set $w = 0$ and $z = 1$, if w is not equal to z. As a consequence we need only two parameters (x and y) to completely specify the game.

Upon changing x and y we will get different games. Four qualitatively different games can be identified. If $x \in (1.0, 2.0)$ and $y \in (0.0, 1.0)$ we have a game that is known in biology and evolutionary game theory as the "hawk-dove" game. In political science and economics the game is better known as the "chicken" game; sometimes this game is also referred to as the "snowdrift" game. In biology this game formalizes a situation in which there is a competition for a shared resource and the contestants can choose either conciliation or conflict. In game theory this game is known as a canonical model of conflicts between two players and has been the subject of extensive research [51, 55]. The hawk-dove game was also used to compare approaches of theory of complex adaptive systems and game theory to the analysis of systems of interacting players [31].

An example of the payoff space of the hawk-dove game is given in figure 1.2. According to the notation used in figure 1.2, the proposer can choose a letter (A

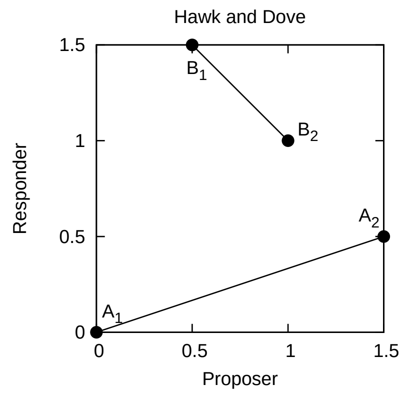

Fig. 1.2: An example of the payoff space of the hawk-dove game

or B) and responder can choose a number (1 or 2). These two choices determine which option out of the four will be implemented (A_1,A_2,B_1 or B_2). The hawk-dove game can be played either in a simultaneous or subsequent setting. In a simultaneous setting the two players make their choices at the same time. In this case neither player knows the choice of the other player. In the subsequent setting the decision of the first player, called proposer, is revealed to the second player, called responder, who can use this information to make his/her decision. The proposer knows that his/her decision will be shown to the responder.

The hawk-dove game is an example of a game in which punishment can be used. Specifically, if option A is proposed, the responder is expected to choose option A_2 because it is more beneficial to him/her than option A_1. However, he/she might sacrifice his/her own benefit to punish the proposer. If option A_1 is chosen, the proposer receives the smallest possible payoff; to avoid this scenario in the future the proposer may want to choose option B, which is more beneficial to the responder.

If $x \in (1.0, 2.0)$ and $y \in (-1.0, 0.0)$ we get the "prisoner's dilemma" [19, 10], a canonical tool to study cooperative behavior in game theory, politics, economics, sociology and evolutionary biology. Many natural processes have been abstracted into models in which living beings are engaged in repeated games of prisoner's dilemma. The iterated prisoners dilemma has been extensively used to study how cooperation can arise in nature as a result of evolution. Martin A. Nowak in his review utilized prisoner's dilemma to discuss five mechanisms for the evolution of cooperation: kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection [45].

In this game players need to make a choice between two actions that are called "cooperation" and "defection". An example of the payoff space of the prisoner's dilemma is given in figure 1.3. Like the hawk-dove game, the prisoner's dilemma can be played in both subsequent and simultaneous settings. The main idea behind the prisoner's dilemma is that defection is always more beneficial than cooperation, independent of the strategy chosen by the oppo-

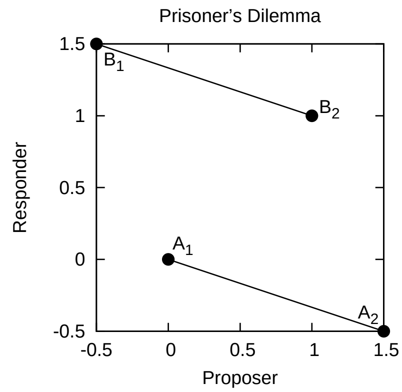

Fig. 1.3: An example of the payoff space of the prisoner's dilemma

nent. On the other hand, mutual cooperation of the players is more beneficial to both players than mutual defection. Because of these two properties the game presents players with a dilemma between cooperation and defection.

The prisoner's dilemma is an example of a game in which a rewarding behavior can be observed. In particular, when the responder needs to choose between options B_1 and B_2 he/she might choose option B_1 because this option is more beneficial to him/her than option B_2. However, in this case the proposer will receive the smallest possible benefit (-0.5) and, as a consequence, it is very likely that in the next round of the game he/she will not propose option B, which is beneficial to the responder. To prevent this scenario, the responder can sacrifice his/her own benefit (by choosing option B_2 instead of B_1) to reward a good proposal made by the proposer. This will motivate the first player to propose option B in next rounds of the game.

If $x \in (0.0, 1.0)$ and $y \in (-1.0, 0.0)$ we get the "stag-hunt" game which describes a conflict between safety and social cooperation [59, 61, 60]. This game is also known as "assurance game", "coordination game", and "trust game". Several animal behaviors have been described as stag-hunts including coordination of slime molds and hunting practices of orca whales. An example of the payoff space of this game is shown in figure 1.4. In this figure we used the same notation as in the prisoner's dilemma. In contrast to the prisoner's dilemma and the hawk-dove game, the stag hunt game is only relevant in the simultaneous setting. In the subsequent setting a rational proposer should always choose pair $B_1 - B_2$ because he/she knows that in this case responder will chose option B_2 which is the most beneficial option for both players. In the simultaneous setting the first and second players are expected to choose option B and 2, respectively, since in this case both players will get the maximum possible payoff. However, this strategy is risky for both players. For example, if the first player chooses B and the second player chooses 1, the first player will end up with the worst possible option for him/her (B_1). Thus for the first player option B can be considered a risky one. In contrast, option A can be considered as safer because

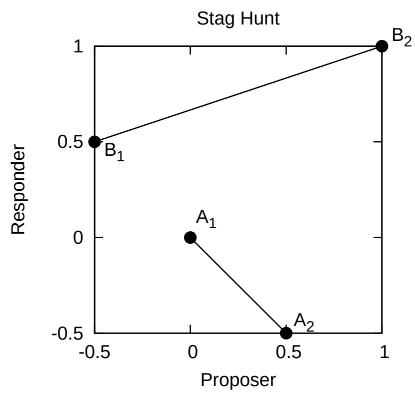

Fig. 1.4: An example of the payoff space of the stag hunt

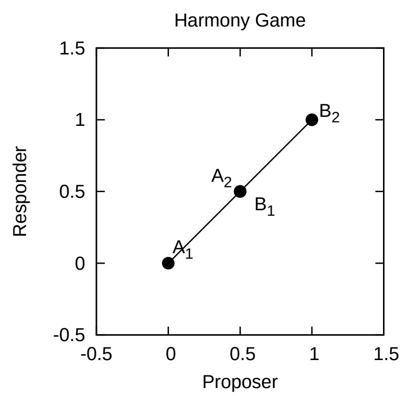

Fig. 1.5: An example of the payoff space of the harmony game

even in the worst case scenario (the second player chooses option 1), the first player does not lose anything. Applying the same logic, we can conclude that choices 1 and 2 are safe and risky choices, respectively, for the second player. Thus it can happen that both players try to avoid risk and, as a result, they end up in option A_1, in spite on the fact that option B_2 would be more beneficial for both of them.

If $x \in (0.0, 1.0)$ and $y \in (0.0, 1.0)$ we get the "harmony" game. This game is trivial since it does not induce any dilemma. It is considered merely for the completeness of the classification. An example of the payoff space of the harmony game is shown in figure 1.5.

1.4 Performed Experiments

The methods developed in this thesis were tested on data collected during two experiments. For the first experiment we have created a web site where users could play a game with each other (the game will be described in more detail later). This experiment will be referred to as the "web based" experiment. This experiment utilized 27 participants; nine teams of three players each were formed. Teams played different numbers of games (ranging from four to 24). The average number of games played by one player was 12.4. In total 112 games were played. The teams were formed by self selection and mutual agreement of team members. The players in a team knew each other since the main intention of our study was to develop a method for monitoring cooperative aspects of interpersonal relations. The composition of the teams was the same for the entire experiment.

The participants for the web-based experiment were recruited by advertising the experiment on the Eindhoven University of Technology campus. We also asked the interested people to participate in the experiment with their friends or relatives. There were 17 male and 10 female among the 27 participants. Participants of six different nationalities were involved in the experiment: 14 Dutch, six Ukrainians, four Russians, one Salvadorian, one Moldavian, and one Iranian. The average age of the participants was about 30 years. The youngest and the oldest participant were 19 and 54 years old, respectively. Twenty participants out of 27 were between 25 and 32 years old, inclusively.

The second experiment considered in this work was performed as part of the Mars-500 isolation experiment. The Mars-500 experiment was organized by the Institute of Biomedical Problems in Moscow. During this experiment six participants have been isolated for 520 days to simulate a flight to Mars. Every other week the six participants took part in our experiment for approximately 30 minutes. During these sessions the crew members interacted with each other through a computer-based environment. In particular, for approximately the first ten minutes of a session they played with each other the same game that has been used in the web-based experiment. As in the web-based experiment each team consisted of three participants and the composition of the teams did not change for the duration of the experiment. The two teams played 32 and 33 games respectively. The experimental sessions were separated by two weeks, with two exceptions. First, the time separation between experiment 18 and 19 was four weeks due to the simulation of a landing on Mars. Second, data for experiment 18 are not available for unknown reasons. The first experiment was conducted on June 12, 2010 and the last one on September 17, 2011.

The Mars-500 experiment was a long-term experiment with a slow generation of data (two teams played one game every two weeks). Moreover, there was a large delay (up to six months) in our receipt of the data from this experiment. Taking these facts into account, we decided to conduct the web-based experiment to generate preliminary data for development of methods for analysis of the data from the Mars-500 experiment. We did not plan to compare the results of the two experiments with each other since there are many different factors that make these experiments different (and isolation is just one of them). As a consequence, it would be impossible to determine a reason for any difference between the results from the two experiments. Moreover, if isolation was the only different factor between the experiments, one comparison between isolation- and no-isolation-experiments would be insufficient to conclude that the observed difference between these experiment is conditioned by isolation.

2. COLORED TRAILS GAME

One of the goals of this work is to develop a method for monitoring cooperative behavior through analysis of the regular interaction of crew members with each other through game play. Using a game for the above mentioned purposes imposes certain requirements upon the game. In this chapter we list these requirements and justify our choice of the game in the context of these requirements. We also present the rules of the game in detail and propose a generalization of these rules that makes the game more suitable for purposes of this research. Additionally, we put the chosen game in the context of other well known (canonical) games and discuss the differences and similarities between these games. Finaly, we present a method that allows us to tie decisions of the players in the game with their strategies (social preferences) in a straightforward way. To do that we predefine several possible strategies in the game and make sure that the payoff space of the game is constructed in such a way that different pure strategies result in different decisions.

2.1 Why Colored Trails?

The choice of the game for monitoring cooperative behavior was dictated by the following criteria:

- Simple enough for analysis
- Rich enough to reflect features of real life interactions
- Grounded in a situated task domain
- Strategic (i.e. partial information that promotes strategic reasoning)
- Specially developed to study social interactions

Colored Trails (CT) is a multiplayer negotiation game that can be classified as a computer version of a board game involving strategic and logical reasoning. The CT game is a common name for a broad range of games utilizing the same representation of the game situation. Instead of an abstract payoff matrix, the CT games represent situations by a colored board on which players and their goal are located. Players can have different resources, represented by the colored chips, that can be used by players to move on the board and, in this way, to reach or come closer to their goals. The interaction between the players is introduced by giving them a possibility to exchange their resources (chips). So we can say that the CT game resembles real life situations in which people have different goals and need some resources to reach these goals. In the initial state of the game players can be in different situations and, therefore, require different kinds of resources to reach their goals. In other words, resources of different kinds can have different values to different players. A redistribution of the resources can be done as a result of negotiations between the players. The game is interesting for analysis since it contains both competitive and collaborative components.

The ways in which the above described representation is used varies a lot. For example, some information about the state of the game can be hidden, such as the current location of the opponent, the location of his/her goal and the chips owned by the opponent. The scoring function can also be constructed in different ways. It can depend on the final locations of the players and their remaining chips in different ways. In particular, the scoring function of a given player can be dependent (or not) on the final location of his/her opponents and/or the remaining set of opponents' chips. The games can also be different in the way the negotiations are organized. For example, the number of negotiation rounds can vary. The player can have (or not) a freedom to choose an opponent. The players can be forced (or not) to follow the agreement achieved in the negotiations and so on.

Moreover, after the rules of the game completely fixed, every single CT game is different from the other games by location of the player and the goal on the board, by the coloring of the board and the sets of chips owned by players. This difference can lead to qualitatively different situations and qualitatively different types of social dilemmas. In this sense the CT game is different from such simple games as prisoners dilemma, ultimatum game or dictator game, in which the payoff matrix is simple and fixed.

The CT game provides a flexible setting that allows researchers to vary the complexity of the game, the level of dependence between players, and the accessibility of information about the state of the game. This game has been developed at Harvard University [20] to study humans' decision making process and has been used by many researchers studying human human and human-agent interactions

The CT game was used to evaluate different decision-making models that represent, learn and adapt to various social preferences that influence decision-making of people [20, 24, 27]. For example the CT game has been used to predict bidding behavior in negotiations [24]. Specifically, different social factors (individual benefit, aggregate benefit, advantage of outcome and advantage of trade) associated with the options have been used as an input for a training of a machine learning algorithm predicting decisions of proposers. Results of this study show that an algorithm that considers options in the context of other options is significantly more successful than an algorithm that considers options independently. The machine learning approach in combination with the social factors associated with the options in the game have also been used to learn and predict behavior of people playing as responders [27]. The trained algorithm has been used by computer games playing as proposers. In particular, the computer agents proposed those options that had the highest probability of being accepted by people according to the trained model. The computer agents constructed in this way outperformed agents playing the Nash equilibrium strategy as well as humans. Some researcher have also use the CT game to develop and test computer agents that are able to model and adapt their behavior to strategies exhibited by people from different cultures [23, 33, 32].

The CT game has been used not only to construct agents that are able to adapt to behavior of people but also to study how people adapt to agents playing different strategies. In particular researchers studied the effects of cooperative agent behavior on human cooperativeness [67]. This study shows three main findings: (1) humans tend to be more cooperative towards cooperative agents and do not fully exploit altruistic behavior, (2) humans play less cooperatively towards egoistic agents and (3) egoistic agents are often perceived as humans.

The CT game has also been used to study human-agents teamwork in dynamic environments and to investigate difference between people behavior towards other people and agents [66]. In this study people could form team by negotiating over the division of a reward for the successful completion of a group task. Participants could also choose to defect from their existing teams in order to join or create other teams. The results of this study show that when people form teams, they offer significantly less rewards to agents than they offer to people. On the other hand, the study also showed that there is no significant difference in people's rate of defection from agent-led teams as compared to their defection from human-led teams.

In the field of agent-agent interactions the CT game was used to develop and test a computational model of helpful behavior that could be used by computer agents during interaction with each other [62]. In the developed model helpfulness is characterized in terms of cooperation and reliability. The computer agents using the developed model of helpfulness choose their actions based on their estimate of others' degree of helpfulness. Results of this research show that agents using the developed model could identify and adapt to others' varying degree of helpfulness and, in this way, they could outperform agents who did not used this model. Other researchers use the CT game to evaluate different mechanisms of helpful behavior embedded into computer agents interacting with each other in environments with varied agents' uncertainty about the world, each others' capabilities, resources or the cost of helpful behavior [35].

Researchers also have used the CT game to study how social preferences are influenced by interpersonal relationships and task-dependencies in interactions between people [40]. Specifically, the CT game was played between two players who knew each other (friends) and by strangers. Moreover, two types of task-dependencies have been considered: (1) one of the players could reach his/her goal without a chips exchange and (2) both players needed to perform a chips exchange to reach their goals. This research demonstrates that friends play the game differently from strangers and player-dependence status affects some outcomes.

A form of the CT game can be played as a revelation game in which players may choose to reveal or keep secret their private information (for example goals) before engaging in multiple rounds of negotiations about an exchange of resources (chips) in the game. This form of the game has been used to develop and test computer agents that are able to model the social factors that affect the players' revelation decisions on people's negotiation behavior [49]. The results of this study show that agents utilizing the introduced agents outperform people and agents playing Nash equilibrium strategies. The results of another study of a goal revelation game show that those who choose to reveal their goals outperform negotiators in the same setting that forbids revelation. In addition, goal revelation has a positive effect on the aggregate performance of negotiators, and on the likelihood to reach agreement [21].

The CT game also has been used to parameterize and evaluate a computational model of reciprocity, that represents reciprocity as a compromise between two social factors: the extent to which players reward and punish others' past actions (retrospective reasoning), and their estimate about the future consequences of their own actions (prospective reasoning) [26]. This study shows that agents reasoning about reciprocal behavior of people significantly outperform agents that do not reason about reciprocity.

Other researchers used the CT game to illustrate the performance of a model of strategic reasoning that allows researchers to distinguish between the player's utility function and his/her beliefs about the utility function of his/her opponent and the player's beliefs about how his/her opponent might interact with yet other opponent [18]. In this study authors demonstrated that players have slightly incorrect beliefs about other players in the game. The effect of partial information on humans reasoning about others has also been studied using CT game [17]. In this study authors provide an experimental proof of the fact that people do reason about other players. The computer agents using the developed model of reasoning about others demonstrated better performance in the interactions with people.

The CT game was used to test a novel method for helping humans make good decisions in complex games [1]. In this study authors used theory of reasoning patterns to create computer programs capable of generating advises for human players based on the mathematical description of a game. This study shows that humans who received advises performed better than those who did not.

The settings of the CT game are more complex than the settings of the canonical bilateral games such as prisoner's dilemma, stag hunt and ultimatum game. This property of the CT game has been used to present a method for description and analysis of strategic interactions in complex settings by reduction of complex interactions to a set of bilateral normal-form games [9].

The representation of the game situation provided by the CT game has been used to investigate the way the representation of a game affects the behavior of people and the performance of computer agents that interact with people in such environment [22]. Specifically, the CT game was used to provide the so-called task context, in which the game was formulated in terms of goals and resources. The behavior of players in the task context has been compared with the so-called abstract context, in which the game was given in terms of the payoffs of the decision choices. It has been demonstrated that people are more helpful, less selfish, and less competitive when making decisions in task contexts than when making them in the abstract contexts.

In the Mars-105 experiment the CT game was used to investigate its potential in measuring social dynamics in small isolated groups of people performing long term missions [34, 68, 52].

In our study we have used the CT game to measure cooperative behavior of players. Our research provides the following three contributions to the CT game community. First, we have proposed to use a special class of the payoff spaces that create a dilemma between cooperation and two types of fairness and, in this way, help to identify social preferences of players. Second, we have proposed two numerical ratios that describe cooperative behavior of players. Third, we have considered the combinatorial complexity of the game and its influence on the choices of the players in the game. In particular, we have identified three sources of the combinatorial complexity of different options and have demonstrated that they influence the probability of options to be noticed (and proposed) by players. We have also proposed a method a method to determine social preferences of the players that takes into account the fact that some options can be unnoticed by players because of their combinatorial complexity.

One of the advantages of the CT game compared with the simple canonic games (such as prisoner's dilemma or ultimatum game) is that the payoff matrix of the CT game is not fixed (it varies from game to game) and, in this way, we can cover a broader range of social dilemmas. By analyzing decisions of the players in different situations we can learn more about the social preferences of the player. Moreover, in CT game the players have many more options to choose from (usually dozens of choices) and, as a result, a single choice of a player is much more informative then a choice of one option out of two or several options.

Another advantage of the CT game is that we can control the settings of the game (by changing the coloring of the board, allocation of the chips and locations of the players and the goal on the board). So, we can change the payoff space in a way that is more relevant to our research questions.

Moreover, our work is not purely research work. In particular, we needed to care about usability of the designed system. Therefore, we needed to choose a game that is perceived by players as a real game and that is interesting to play. The CT game is better in this sense than the simple canonical games since it provides a nice (not very abstract) representation and it has a logical component; players need to think to figure out what options in the game they have.

On the other hand, we needed to choose a game that is relatively easy to analyze. This is the reason why we could not use some complex strategic video games. The CT game looks like a good balance; it is complex enough to be interesting to players but still simple enough to conduct reasonable analysis of the data generated by the players.

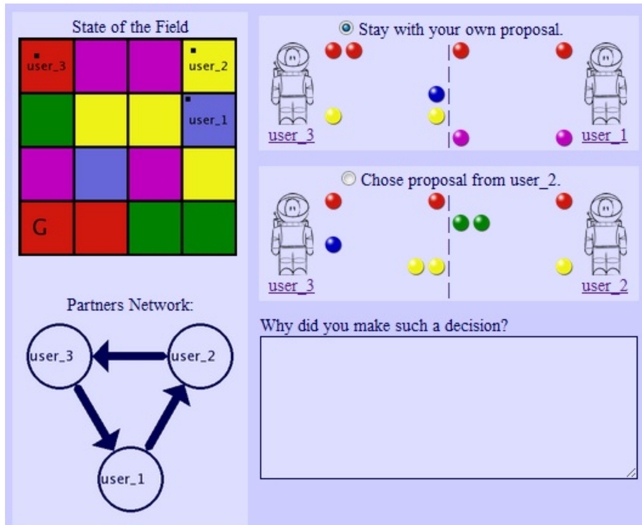

Fig. 2.1: Example of the colored trails game on the response phase.

2.2 Rules of the Game

The game is played on a rectangular board composed of colored squares (see figure 2.1). Colors are chosen from a fixed set of colors. At the beginning of the game every player is placed on one of the colored squares of the board and receives a set of colored chips (resources). The colors of the chips are taken from the same set as the colors of the board squares. Additionally, one square on the board is designated the goal-square. Players can move on the board using their chips. In more detail, they can make a horizontal or vertical step to one of the neighboring squares if they have a chip of the same color as the new square. 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. More specifically, after the negotiations the computer performs the best possible move for every player taking into account the initial location of the player, location of the goal and chips owned by the player. After the moves are performed, the points of the player are calculated in the following way: for every remaining step to the goal square a player is penalized 25 points (in other words, 25 points are subtracted from the player's score), and for every remaining chip player receives 10 points; a players also receives 125 points to avoid negative payoffs.

Before making their moves players are allowed to exchange some of their chips with another player. During the course of the game, any exchange of chips is possible if both participants of the exchange consent to it.

The negotiations can be organized in different ways. In the Mars-105 experiment players had predefined roles: two proposers and one responder. The proposers were allowed to offer any exchange they wanted and the responder was free to choose one of the offers or reject both. For the Mars-500 experiment, we proposed a generalization of this negotiation scheme. In the generalized version of the game every user plays as proposer. Moreover, in contrast to the previous version of the game, proposers were free to choose a player (responder) whom he/she wanted to offer a chips exchange. As a result of these modifications, two or three players will play the responder role in the second stage of the game.

These modifications provide several advantages. First, we increased the number of proposers per game (from two to three) and, as a result, we get more data about the behavior of proposers. Second, we increased the number of responders (from one to two or three). This way more information about behavior of responders can be collected. Third, we increased the variety of situations in which responders can be. In particular, responders have to choose from different numbers of offers coming from proposers who are in different situations. Fourth we added a phase to the game, that is aimed to assess irrational preferences of the players. At this stage, when each player is choosing a partner for a current game, the player's behavior cannot be based on rational thinking about the state of the game (because it is not known) and, as a result, the choices of the partner are either random or are based on some interpersonal preferences.

The size of the board and number of colors are the main factors determining the complexity of the game. The game can be not interesting if it is too trivial or too complex. Trying to achieve a reasonable complexity we decided to use a four-by-four board and five colors. Our further web-based experiment has demonstrated that in about 30% of cases proposers made non-Pareto optimal decisions (*i.e.*, there were offers that provided better payoffs for both proposer and responder than the proposed offer did). In 70% of case the players were able to find Pareto optimal decisions. These numbers prove that the game was not trivial (not all offers were Pareto optimal) but also not extremely complex (majority of the offers were Pareto optimal).

2.3 Relation to Canonical Games

Let us position the considered version of the CT game among the games that are usually used in game theory and experimental economics to study cooperation and fairness. The prisoner's dilemma game [19, 10] is a canonical game to study cooperative behavior. A schematic representation of this game is given by its payoff space shown in the most left tab of figure 2.2.

The first player, called proposer, can propose either the cooperative pair of options (B_1, B_2), or the defective one (A_1, A_2). The second player, called responder, can, in his/her turn, choose one of the options from the proposed pair of options. The first option in the pair (A_1 or B_1) is the defective choice and the second option (A_2 or B_2) is the cooperative one. As we have mentioned in one of the previous sections, the main idea behind the prisoner's dilemma game is that the defective strategy is always more beneficial than the cooperative

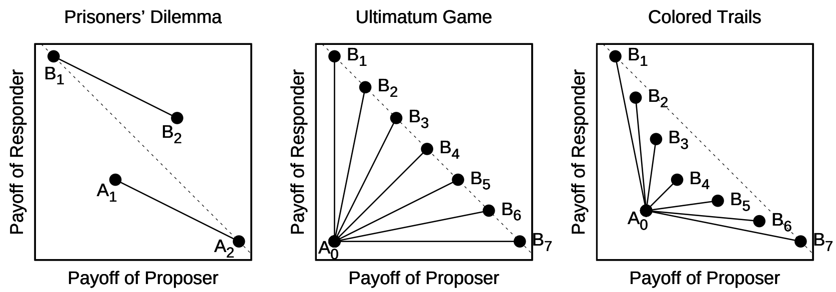

Fig. 2.2: Schematic representation of three games: prisoner's dilemma game, ultimatum game and CT game used in this study

one, independently of what strategy is chosen by the opponent (defection or cooperation). On the other hand, mutual cooperation of the players (option B_2) is more beneficial to both players than mutual defection (option A_1). Because of the two above mentioned properties, the game presents players with a dilemma between cooperation and defection. The iterated prisoner's dilemma has been considered as a part of a model that explains how cooperation can arise in nature as a result of evolution [3]. The tit-for-tat strategy has been reported as the best deterministic strategy for the iterated prisoner's dilemma [50] demonstrating that the prisoner's dilemma can be used to explain reciprocity.

The ultimatum game [30] is a canonical game in the study of fair behavior. In this game the proposer offers a split of a known amount of material payoff between two players and the responder decides if he/she wants to accept or reject the proposal. If the proposal is accepted, both players get their part of the payoff. If it is rejected, both players get nothing. The schematic representation of the game is shown in the middle tab of figure 2.2. As in the case of the prisoner's dilemma game, the proposer can choose one of the many available pairs of options and the responder can choose one option from the pair of the proposed options. Option A_0 corresponds to the rejection of the proposal made by the first player. Option B_i corresponds to the acceptance of the proposed allocation of the payoffs. For the responder it is always more beneficial to accept than to reject any proposal that gives a nonzero payoff. So, rational responders are expected to accept any split that provides some positive benefit to them and, as a consequence, rational proposers are expected to propose splits which provide the minimum possible benefit to the responder and the maximum possible benefit to the proposer. However, many experimental studies show that people do not behave like the rational players. People tend to propose and accept only splits that provide a similar (fair) material payoff to both subjects.

In contrast to the prisoner's dilemma game, the considered version of the CT game does not allow players to cooperate within a single game. Specifically, in the prisoner's dilemma game, the responder reciprocates (rewards) the cooperative behavior of the proposer to make the cooperative choice of the proposer beneficial to the proposer. In this way the responder motivates the proposer to cooperate in the future. So, we can say that cooperation can already be observed in a single game (although it is stimulated by the fact that the game will be repeated in the future). In the CT games that we have considered, cooperation is spread over several games. A schematic representation of the game is shown in the right tab of figure 2.2. We would like to emphasize that the shown distribution of the options in the payoff space is just a qualitative example of the CT game. In the considered game, if the first player proposes pair (A_0, B_7) the responder can sacrifice his/her profit for the benefit of the proposer, like in the prisoner's dilemma game, but if these decisions of the proposer and responder are repeated many times the outcome will be very unbeneficial to the responder, in contrast to the prisoner's dilemma game. Such a situation cannot be considered as cooperation because cooperation is understood as mutual help and the described case can be classified as sacrificing behavior of the responder and exploiting behavior of the proposer. In the long run the most beneficial strategy for both players is cooperation, which means that the first player proposes pairs (A_0, B_1) and (A_0, B_7) with equal frequency, and responder chooses option B_i. In this case the two players maximize the total benefit from the game, which is equally distributed between the two players. The CT game also contains the pattern from the ultimatum game, in which the players might be concerned about fairness of the outcomes. In this case option B_4 will be proposed and accepted. As we can see, in the CT game the most fair options (providing equal distribution of the payoffs between the two players) does not coincide with the most cooperative options (maximizing the total benefit of the players). So, we can say that the game creates a dilemma between fairness and cooperation.

The CT game implements just one of many possible collaborative patterns, that focuses on the dilemma between cooperation and fairness. There are many other ways to construct a collaborative game. One of them is to introduce common goals or team goals. For a comprehensive review of collaborative board games see, for example, Zagal *atal*. 2006 [70]. For more detail about collective action and cooperation in general see the "The Logic of Collective Action" by Olson [46].

2.4 Mapping the Payoff Space into Strategies

The CT game is given by the state of the board (how it is colored), the positions of the three players, the location of the goal, and the three sets of chips owned by the three players. Any exchange of the chips between any two players is characterized by payoffs earned by the proposer and responder. Different exchanges can correspond to identical pairs of payoffs. We can say that a set of exchanges represents one "option" if all exchanges from the set are characterized by the same pair of payoffs. In this context, the situation in which a proposer needs to make a decision is characterized by a set of available options. Options available to a proposer can be visualized as dots (a "cloud" of options) in the two dimensional space of payoffs in which the x-axis and the y-axis correspond to the payoffs of the proposer and responder, respectively (see Figure 2.3). One

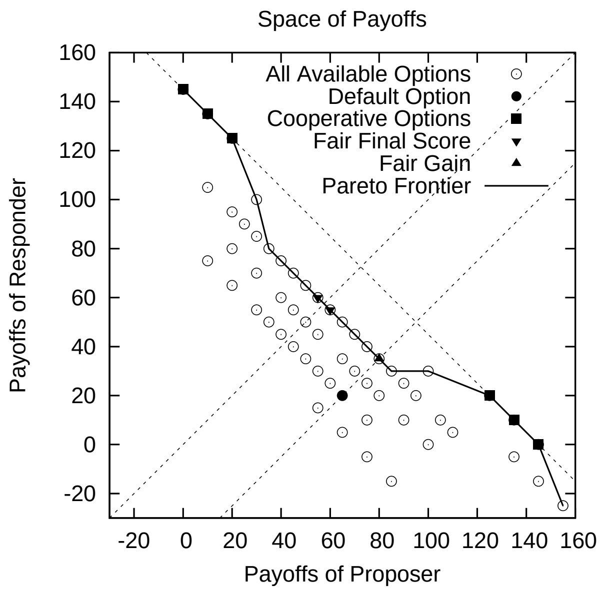

Fig. 2.3: Options available to the proposer in one of the games shown in the payoffs space

available option is no exchange (the "default" option). The default option is also implemented if the proposal of the first player is rejected by the responder.

We assume that proposers value options based on the pairs of payoffs associated with the option. In other words, we assume that there is a utility function $u(p, r)$ that is used by the proposers (explicitly or implicitly) to estimate the attractiveness of different options. A proposer, searching for "the best" exchange, should try to maximize his/her own payoffs (p) and, at the same time, he/she should also try to maximize the payoff of the responder (r) since it determines the probability that the proposed exchange will be accepted by the responder. For this reason, any option which increases both his/her own payoff and the payoff of the responder with respect to another option should be considered a "better" option. We will say that the first option (characterized by its payoffs (p_1, r_1)) dominates the second option (p_2, r_2) if $p_1 \geq p_2$ and $r_1 \geq r_2$ and $(p_1 \neq p_2$ or $r_1 \neq r_2)$.

An option that is not dominated by any other option is called a Pareto optimal option. In a general case there can be many Pareto optimal options (forming a Pareto set). A rational proposer is expected to choose one of the options from the Pareto set. The interesting question is *how* rational players choose from a Pareto set. In any case the chosen option should constitute some kind of a balance between the benefit of the proposer and the benefit of the responder.

We try to identify possible strategies (utility functions) that can be used by the proposers. In behavioral game theory it has been demonstrated that people do not play like game theoretical rational players. In particular, it has been shown that the behavior of humans in game environments can be better described if social factors such as altruism, cooperativeness and fairness are taken into account [24, 27, 67]. One of the most heavily studied models describing the way people combine their own payoff with the payoff of others is the model of Social Value Orientation (SVO) [42]. Recently several good reviews of the SVO models have been published [2]. In its simplest form SVO is defined in terms of the weights people assign to their own and others' payoffs in situations of interdependence. In other words the SVO model assumes that people combine their own payoff with the payoff of others in a liner way:

$$U_p\left(p, r\right) = \omega_1 \cdot p + \omega_2 \cdot r, \tag{2.1}$$

where U_p denotes the utility function of the proposer. Taking into account that a scaling of the weighting factors ω_1 and ω_2 with an arbitrary positive number does not change the model and using a normalization condition $\omega_1^2 + \omega_2^2 = 1$, we can rewrite the model in the following way:

$$U_p\left(p, r\right) = \cos\left(\alpha\right) \cdot p + \sin\left(\alpha\right) \cdot r, \tag{2.2}$$

Different values of angle α correspond to different social value orientations of people. In social psychology five qualitatively different types of SVO are distinguished:

- Altruistic: Desire to maximize payoff of the other ($\alpha = 90°, U_p = r$).
- Cooperative: Desire to maximize the total payoff ($\alpha = 45°, U_p = p + r$).
- Individualistic: Desire to maximize own payoff ($\alpha = 0°, U_p = p$).
- Competitive: Desire to maximize own payoff in relation to that of the other ($\alpha = -45°, U_p = p - r$).
- Aggressive: Desire to minimize the payoff of the other ($\alpha = -90°, U_p = -r$).

The linear combination of the payoffs of players, used in the above described simple version of the SVO model, assumes that prosocial behavior is conditioned exclusively by cooperative motives (desire to maximize the joint outcome). However, there is strong evidence that people are also motivated by the idea of fairness, which is often modeled as a desire to minimize the absolute difference between the payoffs of players. An extended SVO model incorporating fairness as one of the motives for prosocial behavior was proposed by Val Lange [36].

To be able to distinguish cooperative and fair contributions to the prosocial behavior, special tests have to be designed. The two most common instruments for measuring SVO (triple dominance measure [37] and ring measure [38, 53]) do not provide data necessary for distinguishing between two possible motives behind prosocial orientation. In particular, in the triple dominance and ring measures people need to choose one option from a set of available options. Every option is given by the payoffs allocated to the test person and the other. In both tests the option that correspond to the prosocial orientation maximizes the joint payoff and minimizes the absolute difference between the payoffs. Therefore a prosocial choice may be guided by cooperation, fairness or both.

Like in the case of the two above mentioned measures, we want to use choices of the players in the CT game to determine their social preferences. In most of the cases, if a state of the CT game (coloring of the board, allocation of the chips, positions of the players and the goal) is generated randomly, the choices of the players in the game does not allow us to distinguish between the cooperative and fair preferences. Keeping this in mind we intentionally generated games in which collaborative and fair strategies lead to different non overlapping sets of options. In this way we can clearly distinguish between fair and collaborative strategies of a proposer based on his/her decisions.

Additionally, we have assumed that there are different kinds of fair behavior. Specifically, when people judge different options they might care more about what everybody gets in addition to what everybody already had or, alternatively, they might care more about what everybody will have in the end. As an example, people might think that those who have less in the beginning deserve to get more.

Keeping this in mind we generated games in which the sets of options corresponding to the three earlier defined strategies do not overlap. The utility functions corresponding to the three above introduced strategies can be expressed mathematically in the following way:

- The cooperativeness : $p + r$, where p and r are final scores of proposer and responder, respectively.
- The fairness of the final score: $|p - r|$
- The fairness of the gain from the exchange: $|(p - p_0) - (r - r_0)|$, where p_0 and r_0 are payoffs obtained by proposer and responder in the case where no exchange happens (default payoffs).

An example of the payoff space is shown in figure 2.3. As we can see in the figure, the game provides three non overlapping sets of options. Every set corresponds to one of the predefined strategies: the collaborative strategy maximizing the total payoff of proposer and responder, the strategy leading to a fair gain from the exchange and the strategy leading to a fair final score.

We discovered that only in a very small percentage of the games the three sets of the decisions corresponding to the three predefined strategies do not overlap. So, a random search for the games with this property was very time consuming. To overcome this problem we have used a genetic approach which is described in Appendix 11.1.

3. ANGLE OF BENEFIT

In this chapter we introduce a property, called angle of benefit, that can be used to describe single proposals of players in a way that is very relevant in the context of cooperative and fair behavior. Using this parameter we can reduce the complexity of the decisions made in the proposal phase by focusing on the properties that are important for our study. After this parameter is introduced we calculate it for the proposed and not proposed options to demonstrate that the distribution of this parameter over the proposed options differs significantly from the distribution calculated for the rest of the options. In this way we demonstrate that the property of the options, measured by the angle of benefit, is strongly tied to how the proposers perceive different options. We also present decisions of the participants of the Mars-500 experiments in terms of the introduced parameter. Finally, we demonstrate that we can see a statistically significant difference between the decisions of different crew members in terms of the angles of benefit. Moreover, because of the clear meaning of the angle of benefit and simplicity of the statistical properties that we used to describe the sets of angles, we were able to interpret the observed difference between the decisions of the crew members in terms of their cooperativeness.

3.1 Definition of Angle of Benefit

A direct way to describe a proposal is to give a relation between the points gained by proposer and responder in the case where the exchange is realized. This relation can be described by an angle given through the following function:

$$\alpha = \arctan\left(\frac{r - r_0}{p - p_0}\right). \tag{3.1}$$

This angle has a clear interpretation: it gives the direction of the line connecting the default option with the proposed one. In particular, an exchange that is equally beneficial to the proposer and the responder is characterized by an angle equal to 45°. A value between 0° to 90° corresponds to an exchange that is mutually beneficial to both proposer and responder. The angles in the range between 90° and 180° correspond to proposals that are not beneficial to the proposers but are beneficial to the responder (a proposer provides help to a responder). In a similar way, the angles between -90° and 0° describe situations where proposers ask for help (*i.e.* a proposer offers exchanges in which he/she gain points and the responder loses his/her points).

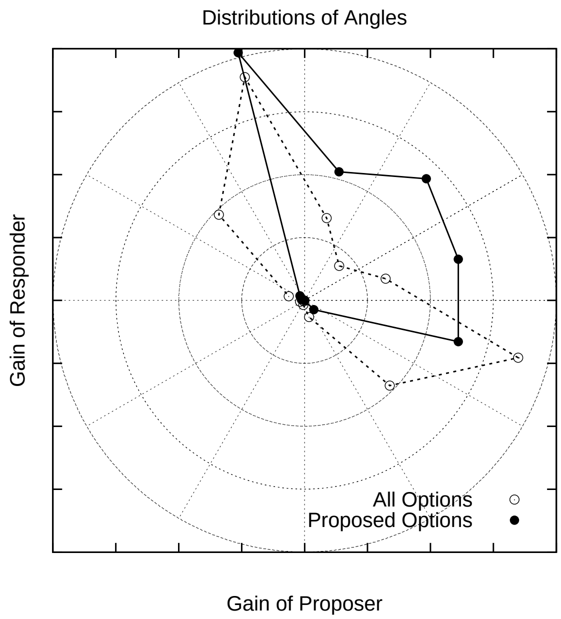

Fig. 3.1: Distributions of the angle of benefit calculated over all available options as well as options chosen by proposers.

As in the previous section, we analyze how the distribution of the angle of benefit is influenced by the decisions of the proposer. In figure 3.1 the distribution of the introduced angle over all available options and over options chosen by the proposers is shown. In this figure we can see a clear and expectable influence of the proposers decisions on the distribution of the angle. Proposers tend to choose options that are beneficial to both participants in the exchange (proposer and responders). We can see that options that are more beneficial to the proposers but still beneficial to the responder (angles between 0° and 45°) slightly dominate options that are more beneficial to the responders but still beneficial to the proposers (angles between 45° and 90°). We also can see that proposers ask for and propose help. It is interesting to note that proposers offer help significantly more frequently than they ask for it. It should also be noted that proposers practically never propose (or ask for) help for which the cost of the help exceeds the benefit from the help.

3.2 Difference between Players in Terms of Angle of Benefit

In figures 3.2-3.7 we show the dynamics of the angle of benefit of different participants as functions of the session IDs during the Mars-500 experiment. The value of the angle gives the type of the proposal made by the participant (*i.e.*, relation between the payoff of the proposer and responder). The color of the circles in these figures indicates who was chosen as the responder (the person

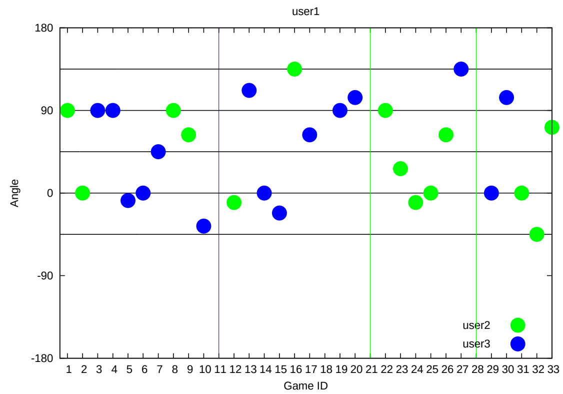

Fig. 3.2: Time dynamics of the angle of benefit for the first participant of the Mars-500 experiment

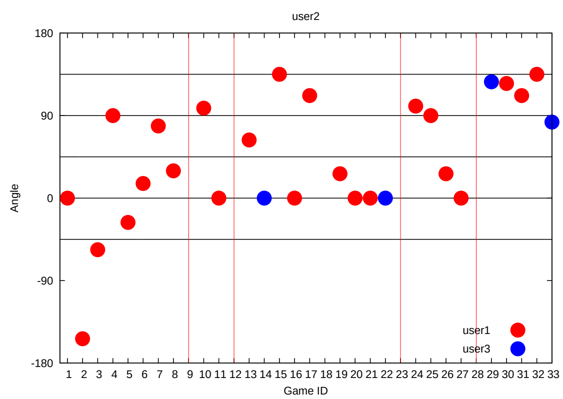

Fig. 3.3: Time dynamics of the angle of benefit for the second participant of the Mars-500 experiment

who has the right to accept or reject the proposal). For some experiments we have a line instead of a circle. In these cases the proposer's and responder's payoffs of the proposal coincides with the payoffs of the default options and, as a result, the benefit angle cannot be calculated since we cannot draw a line through two points that coincide. As in the case of the circles, the color indicates who was the responder.

The first observation that we can make is that some proposers make their proposals to one of the responders much more frequently than to the other one. For example, in the vast majority of cases, the second and the third participants proposed exchanges to the first participant. Similar behavior was also observed in the second team. The fourth participant made his proposals to the fifth participant in all the games except one. This behavior could indicate some psychological preferences. However, in all three cases the preferred responder

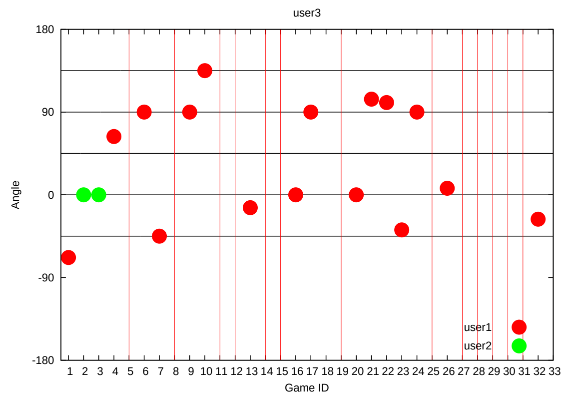

Fig. 3.4: Time dynamics of the angle of benefit for the third participant of the Mars-500 experiment

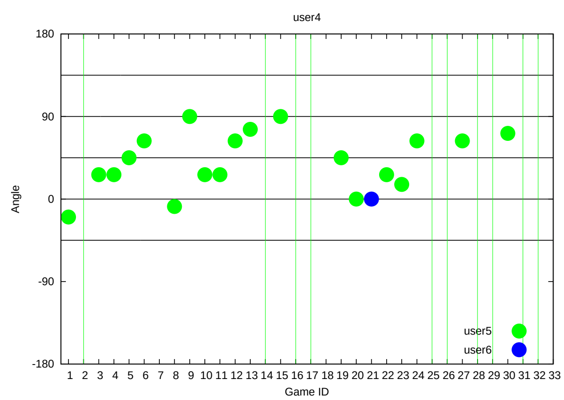

Fig. 3.5: Time dynamics of the angle of benefit for the fourth participant of the Mars-500 experiment

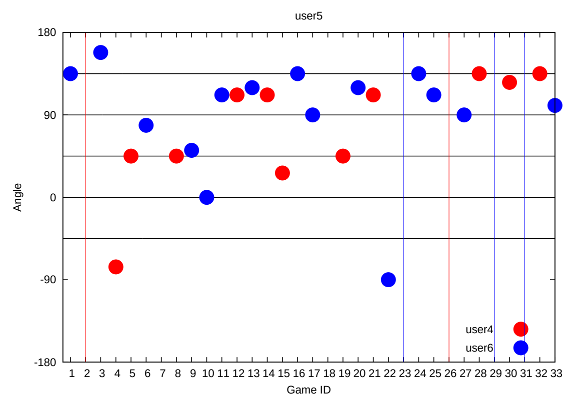

Fig. 3.6: Time dynamics of the angle of benefit for the fifth participant of the Mars-500 experiment

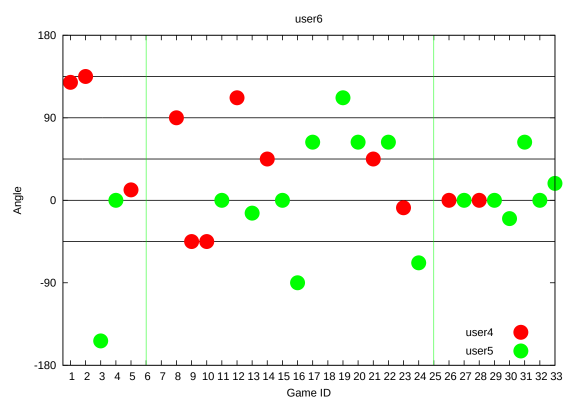

Fig. 3.7: Time dynamics of the angle of benefit for the sixth participant of the Mars-500 experiment

	user1	user2	user3	user4	user5	user6
Average	45.92°	43.26°	32.11°	39.61°	83.20°	17.48°
RMSD	53.19°	66.47°	60.58°	31.69°	61.66°	64.50°

Tab. 3.1: Average values and root mean square deviations of the angle of benefit for the six participants of the Mars-500 experiment

was set by the software as the default option. Thus, it can be the case that the considered users just did not act to change the default choice.

It is interesting to know if any difference between the different proposers in terms of the angle of benefit of their proposals can be seen. Since the angle of benefit is determined by the relation between the payoffs of the proposer and responder, a difference between the players in terms of the angle of benefit would indicate that the players combine their own payoffs with the payoffs of their partner in different ways. Therefore, a difference between the players in terms of the angle of benefit could indicate a difference in social preferences. To compare social preferences of two players we need to find a way to compare the two sets of angles corresponding to these players. In other words, one single angle characterizes one single proposal while the set of the angles can be used to characterize the players' social preferences. The simplest statistical properties that are used to describe a set of values are the average of these values and the root means square deviation (RMSD) from the average. To find out if different players behave differently in terms of the angle of benefit we have tried to use the average and RMSD to describe the set of angles corresponding to different players. The simple meaning of the angle of benefit leads to a simple meaning of the averages and RMSDs. The higher the value of the average is, the more the player cares about the benefit of his/her opponent (responder). If a player has cooperative preferences, he/she will propose help and ask for help. As a consequence, the angles corresponding to his/her proposals will be, in most of the cases, either smaller than 0 or larger than 90 degrees. In contrast, a player who cares only about fairness of the gain will make proposals which give angles close to 45 degrees. It means that in the case of the cooperative player the RMSD will be significantly larger than in the case of the fair player and, accordingly, the RMSD can be used as a rough measure of cooperativeness. The average values and RMSDs corresponding to the decisions of the six participants are shown in table 3.1.

As we can see in table 3.1, the sets of angles corresponding to different players have different values of the average and RMSD. However, in order to state that the players are different in terms of the considered parameters we have to estimate how statistically significant this difference is. In other words, we need to calculate the probability of the null hypothesis stating that all the players play the same in terms of the angle of benefit and the observed difference is just because the sets of angles are not large enough.

To test the null hypothesis we have considered the extreme cases of the largest and smallest averages values and RMSDs. In particular we see that user3 and user5 have the smallest (32.11°) and the largest (82.20°) values of the average, respectively, and user4 and user2 have the smallest (31.69°) and the largest (66.47°) RMSDs, respectively. We have calculated the probability that such a small (large) value can be obtained just by chance assuming that all the players use the same strategy in terms of the angle of benefit. This is accomplished in the following way. We have combined all six sets of the angles into one set and then have randomly chosen 33 values to model decisions of the players (33 is the number of the games played by the participants). For the constructed set we have calculated the average value and RMSDs. This procedure has been repeated 60,000 times. After that we have calculated the number of cases in which the average value was smaller (larger) than the minimal (maximal) average value observed for the real decisions of the participants. As a result we have found that only in 0.055% of cases the average value was as large as or even larger than the maximal value of the average 83.20° corresponding to the decisions of user5. From that we can conclude that such a large average value of the angle of benefits of user5 is very unlikely to happen just by chance. Rather, this result indicated that user5, playing as a proposer, adopts a more sacrificing strategy than all the other players. This feature of user5 is also visible in figure 3.6. In most of the cases this participant makes proposals with the angle of benefit larger than 45°, which means that the payoff of the responder is larger than that of the proposer. Moreover, there are a lot of proposals with the angle of benefit larger than 90°, which means that the proposer (user5) even lost (sacrificed) his/her own points for the benefit of the responder.

We have also found in our test that the average value was as small as or even smaller than the minimal one (17.48°, corresponding to user6) only in 1.83% of cases. This means that it is quite likely that this user has an exploiting strategy. As we can see in figure 3.7 there are many cases (almost 25%) in which the user proposes an exchange with angle of benefit equal to zero, which means that the responder has no benefit from these proposals. Moreover, there are many proposals with a negative angle of benefit, which means that user6 asked the responder to sacrifice his payoff for the benefit of the proposer.

We have also found that the largest value of the RMSDs corresponding to the decisions of user2 can easily arise just by chance. In our test such a large or even larger value was observed in 23% of cases. This finding is also supported by the fact that three other users have a RMSD values larger than 60°, which is close to the maximal one.

Finally, our test has demonstrated that the smallest RMSD corresponding to user4 (31.69°) is very unlikely assuming that all players use the same strategy. The value as small as this or smaller was observed only in $3.33 \cdot 10^{-3}$% of cases. As a result of these tests, we can say with high confidence that user5 is very consistent in his sacrificing behavior. We can also see this in figure 3.6. The larger portion of the angles, corresponding to the decision of this player, can be put into a narrow range between 90° and 135°, which corresponds to sacrificing (or helpful) proposals.

4. LEVEL AND SYMMETRY OF COOPERATION

In this chapter we utilize the angle of benefit introduced in the previous chapter to define two other numerical measures, called cooperation ratios. The two cooperation ratios are defined based on a set of angle of benefits. In other words, an angle of benefit can be used to characterize a single decision while the cooperation ratios characterize sets of decisions and, therefore, they can be used to characterize a given player based on the sets of decisions that he/she made. We start this section from the definition of the two cooperation ratios and explain their meaning. Then we demonstrate how these ratios can be used to visualize cooperative behavior in a team and how to make a recommendation to a team to make its behavior more cooperative. Finally, we estimate the accuracy of the cooperation ratios in different ways.

4.1 Definition of Cooperation Ratios

We found that decisions of different proposers generate essentially different distributions of the angles. To describe the shape of the distribution we split the whole range of the angles into three regions corresponding to quantitatively different situations. The first region corresponds to situations in which proposers propose help (*i.e.*, an offer that is beneficial to the responder and requires some sacrifice from the proposer). The second region corresponds to proposals that are beneficial to both proposer and responder. The third region corresponds to proposals that are beneficial to the proposer and require some sacrifice from the responder (*i.e.*, the proposer asks for help). For every proposer we calculate the number of proposals falling into every of the above defined regions. We will use the following notations: n_{ph} and n_{ah} indicate the number of proposal in which the proposer proposed or asked for help, respectively. The notation n_{mb} represents the number of mutually beneficial proposals. Further, we utilize of the fact that the strategy of a proposer is described by the relative populations of every region. In this way we can decrease the number of parameters describing the behavior of proposer (from three to two). In other words, we can remove the degree of freedom that represents the number of played games while preserving the information about behavior of the proposers. Accordingly, we introduce the following two parameters:

$$\nu_{cl} = \frac{n_{ah} + n_{ph}}{n_{mb} + n_{ah} + n_{ph}}, \tag{4.1}$$

"level of cooperation", gives the portion of proposals in which proposer proposed or asked for help.

$$\nu_{gr} = \frac{n_{ph}}{n_{ah} + n_{ph}}, \tag{4.2}$$

"give ratio", indicates how frequently a proposer proposes help in all those situations when help is involved.

We assume that the values of the two introduced parameters (ν_{cl} and ν_{gr}) depend on the identity of the proposer as well as on who is the responder. So, the behavior of every proposer can be described by two pairs of the considered parameters (corresponding to two responders).

4.2 Team Diagrams

An example of a diagram visualizing cooperative behavior in a team, in terms of the two cooperation ratios, is shown in figure 4.1. The shown diagram is built based on the data generated by one of the teams participating in the web-based experiment. Every player is represented by two points (two pairs of cooperation ratios), because every player has exactly two partners and his/her strategy can depend on who his/her partner in the game is. The two points corresponding to one player are always connected by a red line. Blue lines are used to indicate a responder corresponding to a point representing behavior of a proposer. In other words, red lines represent subjects and blue lines represent interpersonal relations between the subjects. In terms of the introduced diagram the "healthiest" relations in the group would be represented by a point located on the very top of the figure (the highest cooperation) and in the middle of the horizontal direction (proposer proposes help as frequently as he asks for it).

As we can see in the figure, players could exhibit significantly different behavior in terms of the two cooperation ratios. Moreover, behavior of a player could be different depending on who the responder is. In this way we can potentially capture some cooperative aspects of interpersonal relations.

The clear meaning of the two cooperation ratios provides a simple interpretation of the diagrams. For example, in figure 4.1 we can see that one of the players (the C_2-player) shows the maximal level of cooperation. However, the give-take ratio of this player is too high indicating that this player almost always proposes help. For this player we could recommend that he/she asks for help when it is more beneficial for the whole group to do so. In the same team we can see that the second player (B_2-player) exhibits different behavior depending on who the responder is. This player is more cooperative with the most cooperative player (C_2-player) and less cooperative with the least cooperative player (A_2-player).

We would like to distinguish between different types of preferences. The proposer has certain preferences over possible allocations of payoffs between himself/herself and his/her opponent (original preferences). However, the proposer understands that an allocation of the payoffs is not only determined by his/her choice but also by the choice of the responder and the rules of the game

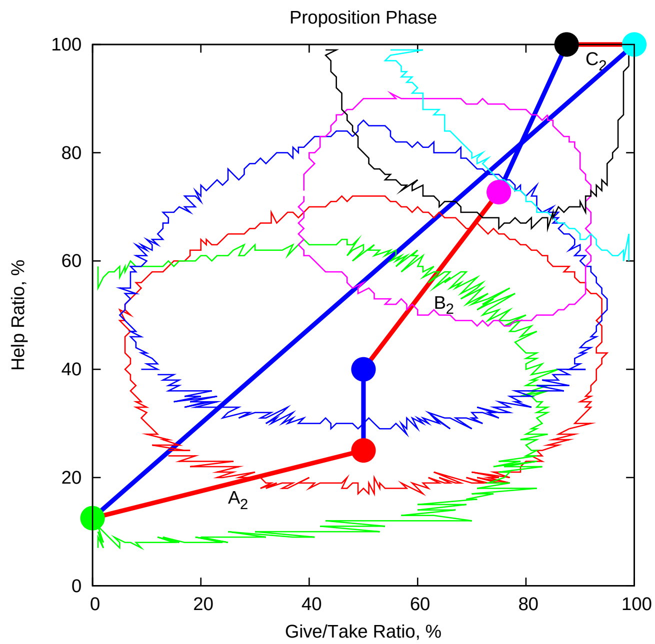

Fig. 4.1: Strategies of players in team 2 given by values of the "give/take" and "help" ratios.

that dictate how the choices of the players have to be combined. This means that decisions of the proposer are not only conditioned by his/her original preferences over the options but also by his/her beliefs about the preferences of the responder. In other words, the proposer creates new preferences over the options in the game by combining his/her original preferences with his/her beliefs about the original preferences of the responder. In this work we do not try to study how the new preferences of a player are determined by his/her original preferences, belief about the preferences of the opponent and setting of the interactions (rules of the game). Instead, we propose a method to measure and describe the new preferences of the player in the given conditions.

4.3 Accuracy of Cooperation Ratios

The limited number of the games raises the question of the accuracy of the cooperation ratios. To address this question we have numerically calculated the probability density function (PDF) giving the probabilities of different values of the two cooperation ratios of a player based on a given set of his/her decisions. Specifically, we have randomly generated models of proposers. Every model was given by the probabilities of the three different kinds of decisions (propose help, ask for help, propose mutually beneficial exchange). Every probability was generated by the random number generator implementing uniform distribution between 0 and 1. The generated probabilities were normalized to make the sum of the three probabilities equal to 1. Every model (random decisions generator) was used to generate the same number of decisions as in the considered observed set of decisions (made by a player). The model was accepted if the generated and observed decisions gave the same population of the three kinds of decisions. In this way, for every observed population of the decisions (given by the give and help ratios) we have generated one million models that were used to construct the PDF of the models. For every generated PDF we have calculated the cutoff value such that integration of the part of the distribution with the values larger than the cutoff should give 0.9. In other words, we found the region around the maximum of the PDF such that the probability for the real model to be within this region is equal to 0.9. These regions are shown in figure 4.1 with the lines surrounding the corresponding points. As we can see in this figure, the difference between the observed values is very unlikely to be produced purely by the inaccuracy of the measurements.

Additionally to the above described visualization we have estimated the statistical significance of the difference between the cooperation parameters of different players. In particular, we have considered all possible pairs of the players, and for every pair we have calculated the Euclidian distance between the ratios corresponding to the two compared players. The two ratios corresponding to a player have been considered as a point in a two dimensional space and the difference between any two given players has been calculated as the Euclidian distance between the two points representing the two compared players. We will call this distance a "reference distance" because it corresponds to the original (real) decisions of the players and will be used later in the comparison with the distances corresponding to the "fake" decisions. The calculated reference distances have been used to estimate the p-values of the null hypothesis that the decisions of the two compared players are statistically indistinguishable. In other words, for every pair of players we have calculated the probabilities that the corresponding reference distance between the players is caused by the fact that the sets of decisions are just not large enough. These p-values have been calculated in the following way. We have combined the decisions of every pair of players into one set. The combined set has been randomly re-split into two new subsets such that the sizes of these subsets were the same as sizes of the two original sets. The distance between the two new sets has been calculated. We will call this distance a "fake distance", because it corresponds not to the real but to a fake (random) split of the set into two subsets representing two compared players. This procedure has been repeated many times to calculate the portion of the cases in which the fake distance was larger or equal to the reference one. This portion is nothing but the p-value of the null hypothesis stating that decisions of the two compared players are statistically indistinguishable. Under the assumption that the players behave in the same way, we have calculated the probability that the observed distance between the two given players can be as large as it is or even larger just by chance. In total we have considered 348 pairs of players. For every pair the fake distance has been compared with the reference distance 100,000 times. We found that for three pairs of players the fake distance was never as large as the reference one. For nine pairs of players the fake distance was equal to or larger than the reference distance in less than 10 out of 100,000 cases. This means that for these cases the p-value is less than 10^{-4}. For 25 pairs the fake distance was as large or larger than the reference distance in less than 100 out of 100,000 cases (p-value is less than 10^{-3}). For 50 pairs of players the p-value was less than 10^{-2}. The small p-values cannot be explained by the fact that just few players are different from the rest. For example, among the 50 pairs of players with the p-values smaller than 10^{-2}, the most frequent player was present in 23 pairs. So, if we remove this player out of the consideration we still have 27 pairs of players that are statistically different. If we remove the second most frequent player from the consideration, which was found in nine pairs, we still have 19 pairs of the players who are statistically different from each other. If we remove the third and fourth most frequent players from the consideration, both of which were present in seven pairs, we have seven pairs of players who were statistically different from each other (with the p-value smaller than 10^{-2}).

4.4 Remark about Reciprocity

In this section we briefly discuss the possible effect of reciprocity and how it relates to the approach described in this chapter. Reciprocity is understood as a desire to award good and punish bad behavior of the opponent. The main logic behind the rewarding and punishment is to motivate the opponent to continue his/her good behavior and stop his/her bad behavior, respectively.

The effect of reciprocity in the Mars-500 experiment is expected to be significantly weakened by the following two facts. First, the subsequent games were separated by at least two weeks. Second, between the games the participants interacted with each other very intensively since they lived together in a very confined environment. So, a lot of good or bad things could happen between two subsequent games. Therefore, a player could reward or punish another player in the CT game not because of the previous game but because of something else that may have happened between the two subsequent games.

We also would like to note that players could certainly be driven by reciprocal motives and these motives are not in contradiction with the idea of social preferences (given either by the cooperation ratios or by a utility function, in a more general case). The desire to reward or punish just changes the utility function. Therefore, to model the effects of reciprocity we have to assume that the utility functions of players are time dependent (and we believe that it is definitely a good assumption). However, with the proposed method we are not able to see this time dependency because we need many decisions (many games) to be able to calculate the utility parameters of the players. In other words, we cannot say what the utility function of a given player in a given game was. We have tried to compare the cooperation ratios (and later the utility parameters) describing the players in the first and second parts of the Mars-500 experiment. The difference found was statistically insignificant. However, this does not mean that there is no difference; we are just unable to see it with the current accuracy of the method.

To summarize, we do assume that the social preferences (the cooperation ratios or parameters of a utility function) are time dependent, but with the proposed method we are only able to calculate their values averaged over a large time period. This means that we are not able to say how cooperative a given player in a given game was, but we are able to say how cooperative he/she was on average during the whole experiment (which also provides valuable information).

5. DERIVATION OF UTILITY FUNCTION

In this chapter we derive a utility function that describes fairness and cooperativeness. In the beginning of this chapter we describe the social-welfare [7] and inequity-aversion [16] utilities for the case of two subjects and build a link between these two well known utility functions. Then we demonstrate that the social-welfare and inequity-aversion utilities are generalized to the case of more than two subjects in different ways. We discuss these generalization procedures and propose an alternative (third) way to make this generalization. Finally, we introduce the second type of fairness and incorporate it into the utility function. As a result of this chapter we have a new utility function defined for the case of an arbitrary number of subjects. For the case of two subjects the introduced utility has three parameters that can be used to describe decisions of the proposers in the CT game. Transition from the two ratios of cooperation, introduced in the previous chapter, to the three utility parameters provides a more accurate and general description of the proposers. Moreover, if we have the values of the utility parameters of a player we can explain, to a certain extent, why a given player made a given decision in a given game. This is not the case for the description based on use of the cooperation ratios. So, we can say that a utility based model has an explanatory power while the approach based on use of cooperation ratios has only descriptive power. The utility based approach can be considered also as a more general one since knowledge of utility parameters of a player allows us to estimate the cooperation ratios associated with this player (the opposite is not true).

5.1 Proposer-Responder Settings

Let us consider the proposer-responder setting in the context of a utility function. In the proposal phase the proposer chooses one option from a set of available options. Every option is characterized by two numbers (p and r) that are payoffs of the proposer and responder, respectively. We assume that the proposer (implicitly or explicitly) uses some utility function to estimate "attractiveness" of every option: $u = u(p, r)$. We also assume that attractiveness of options depend on the default payoffs of the proposer and responder p_0 and r_0 (payoffs that will be given to the proposer and responder in the case of no exchange): $u = u(p_0, r_0, p, r)$. In the case of the egoistic proposer, who cares only about his/her own payoff, the utility function is given by the following simple expression: $u(p_0, r_0, p, r) = p$. In many cases (including the game settings that we used) the above given egoistic utility function is too simple to describe the behavior of the proposer adequately. For example, the attractiveness of an option to the proposer might depend not only on the payoff provided by the option to the proposer but also on the probability that the considered option will be accepted by the responder and this probability, in turn, depends on the payoff of the responder.

To describe preferences of subjects in simple test games different utility functions have been proposed. In this study we will consider the simplest utilities based on clear qualitative ideas. The first utility function that we will consider is the "inequity-aversion" utility [16]. This model assumes that subjects are motivated to increase their own benefit (egoistic preferences) and at the same time they are motivated to reduce differences between their own and others payoffs. The second utility that we will consider is called the "social-welfare" utility [7]. It assumes that the subjects are motivated to increase their own benefit as well as the social benefit, caring especially about helping those subjects who have a low payoff.

We would like to note that the utility-based approach is more suitable for modeling decisions in the proposition phase because the attractiveness of every option in this phase is completely characterized by the payoffs associated with it. In contrast, the situation in which a responder needs to make a choice is not characterized completely by the payoffs associated with the available options (for example accept and reject). In addition to the payoffs associated with different options the responder is more likely to take into consideration the payoffs of the options that could be proposed by the proposer. For example, a responder might want to reward or punish proposer depending on what proposals he/she made (good one or bad one). This kind of behavior is known as reciprocity and has been considered by many researchers [25, 6, 15, 57, 11, 8, 13].

5.2 Utility Functions for Two Subjects

Let us first consider the inequity-aversion utility in more detail. For the case of two players it has the following simple form:

$$U_{ia}\left(p,r\right)=p-\alpha\max\left(r-p,0\right)-\beta\max\left(p-r,0\right). \tag{5.1}$$

This utility function has a simple interpretation. The first term represents egoistic preferences of the subjects. Additionally, there are two terms that represent the fact that players do not like unequal distributions of the payoffs (inequity aversion) [16]. It is assumed that subjects do not like situations in which one of the players receives more than another one. It is also assumed that the degree of the dislike of an inequity depends not only on the amount of the inequity but also who is receiving more (me or my co-player). This last assumption is the reason why the utility function has two terms in addition to the egoistic one.

Let us now consider the social-welfare utility in more detail. Charness and Rabin [7] have proposed to use the social-welfare utility function that, for the case of two subjects, has the following form:

$$U_{sw}(p,r) = (1-\lambda)p + \lambda\left[(1-\delta)(p+r) + \delta \min(p,r)\right]. \tag{5.2}$$

As we can see, the social-welfare utility combines the egoistic preferences (the first term) with the social ones (the second term). If the parameter λ is equal to zero, the subject is absolutely egoistic. If λ is equal to one then the subject cares only about the social utility. The social term, in turn, consists of the Hick optimality term and the maximin fairness. The Hick optimality corresponds to the maximization of the total benefit while the maximin fairness motivates the subject to increase the lowest payoff.

Let us now show that the inequity-aversion utility (5.1) coincides with the social-welfare utility (5.2) for the case of two subjects. For that let us find an explicit relation between the parameters of the inequity aversion (5.1) and social-welfare (5.2) utility functions written for two subjects. Before we start to search between the parameters of the two types of the utility functions we first need to ensure that both utility functions are "normalized" in the same way. In other words, we need to remove the ambiguity in the definition of a utility function that can arise from the fact that a decision maker is invariant with respect to the multiplication of the underlying utility by a positive number. For that we consider both utilities for the $p = r$. In this case the inequity aversion utility is equal to p while the social-welfare utility is equal to $p(1+\lambda-\lambda\delta)$. This indicates that the two considered utility functions are different. We can easily see that this difference can be removed if we slightly modify the original social-welfare utility function in the following way:

$$U_{sw}(p,r) = (1-\lambda)p + \lambda\left[\frac{1}{2}(1-\delta)(p+r) + \delta \min(p,r)\right] \tag{5.3}$$

Note the 1/2 in front of the term representing the Hick optimality (cooperative term). After this modification, the social-welfare utility function will be equal to p for $p = r$. This modification can be done by redefinition of the parameters λ and δ in the expression, and it does not change the meaning of the parameters. As before λ represents the portion of the egoistic and social terms in the utility. The λ equal to 1 represents a subject who cares only about the disinterested social utility (*i.e.*, does not care about the personal benefit). In contrast λ equal to 0 represents the egoistic subject. The δ gives the balance between the Hick optimality and maximin fairness. When δ is equal to 1 it means that the subject do not try to cooperate and cares only about the fairness of the outcome. When δ is equal to 0, in contrast, it represents cooperative subjects who do not care about the fairness of the outcome.

To demonstrate that the utilities (5.1) and (5.3) are the same we will consider them for two different cases: $r < p$ and $r > p$. In the case of $r > p$ the inequity aversion and the modified social welfare functions are equal:

$$U_{ia}(p,r) = p(1+\alpha) - \alpha r \tag{5.4}$$

$$U_{sw}(p,r) = \left[1 + \frac{\lambda}{2}(\delta-1)\right]p - \frac{\lambda}{2}(\delta-1)\,r. \tag{5.5}$$

In the case of $r < p$ we have the following expressions for the two utility functions:

$$U_{ia}(p,r) = p(1-\beta) + \beta r, \tag{5.6}$$

$$U_{sw}(p,r) = \left[1 + \frac{\lambda}{2}(\delta+1)\right] p + \frac{\lambda}{2}(\delta+1) r. \tag{5.7}$$

Just from the comparison of the expressions we can see that the two utility functions are identical and the following relation between the utility parameter should hold:

$$\alpha = \frac{\lambda}{2}(\delta-1), \tag{5.8}$$

$$\beta = \frac{\lambda}{2}(\delta+1). \tag{5.9}$$

Just for the record, we also give the inverse relation:

$$\lambda = \beta - \alpha, \tag{5.10}$$

$$\delta = \frac{\beta+\alpha}{\beta-\alpha}. \tag{5.11}$$

The relation between the inequity-aversion and the social-welfare utilities is easy to see if we utilize the fact that both utilities are given by two linear functions one of which is valid for the region $r \geq p$ while another one is valid for the region $r \leq p$. It means that both utilities can be written in the following form:

$$U(p,r) = (1-\sigma)p + \sigma r \quad if \quad r \geq p, \tag{5.12}$$

$$U(p,r) = (1-\rho)p + \rho r \quad if \quad r \leq p, \tag{5.13}$$

$$\tag{5.14}$$

where σ and ρ some real constants. This way writing of the utility functions was given in the work of Charness and Rabin [7]. In this form the utility function has a clear interpretation and the different types of the utility functions correspond to different ranges of the parameters σ and ρ. The inequity-aversion utility is given by the following inequalities: $\sigma < 0 < \rho < 1$. The social-welfare utility corresponds to the following range of the parameters: $1 \geq \rho \geq \sigma > 0$. Additionally, we can mention the competitive preferences that are given by the following inequalities: $\sigma \leq \rho \leq 0$. These preferences mean that the subject always prefers to do as well as possible in comparison to another subject. The visualization of the given relations between the parameters σ and ρ is given in figure 5.1. In addition to the regions corresponding to the three mentioned classes of the utility functions the figure contains four points corresponding to the four special utility functions. The first shown utility function is the egoistic utility that describes subjects who care only about their own benefit. The cooperative utility corresponds to the subjects who put equal weight on

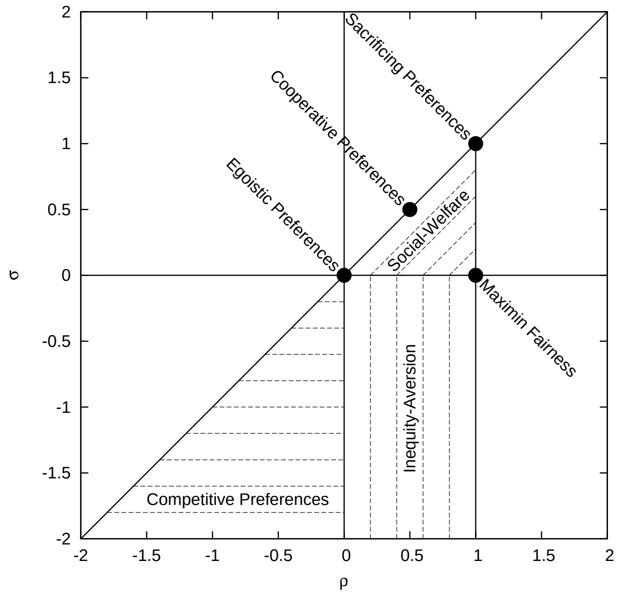

Fig. 5.1: Regions of the parameters σ and ρ corresponding to different classes of the utility functions

each subject's payoff. In other words, these subjects try to maximize the total benefit. The sacrificing utility corresponds to the subject who cares only about the payoff of another subject. Finally, the maximin fairness utility describes subjects who care only about the fairness of the outcome.

Figures 5.2-5.4 show examples of the inequity-aversion, social-welfare and competitive utilities, respectively.

5.3 Utility Functions for More Than Two Subjects

The generalization of the earlier considered utility functions in the case of more than two subjects has been already studied by other researchers. In the work of Fehr and Schmidt [16] which introduces the inequity aversion utility function (5.1) a form applicable to more than two players is also given:

$$U_i = x_i - \frac{\alpha}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} \max(x_j - x_i, 0) - \frac{\beta}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} \max(x_i - x_j, 0) \qquad (5.15)$$

Charness and Rabin [7], who introduce the social-welfare utility function, also give the generalization of the function in the case of more than two players:

$$U_i^{sw} = (1-\lambda)x_i + \lambda \left[(1-\delta) \sum_{i=1}^{n} x_i + \delta \min(x_1, x_2, \ldots, x_n) \right]. \qquad (5.16)$$

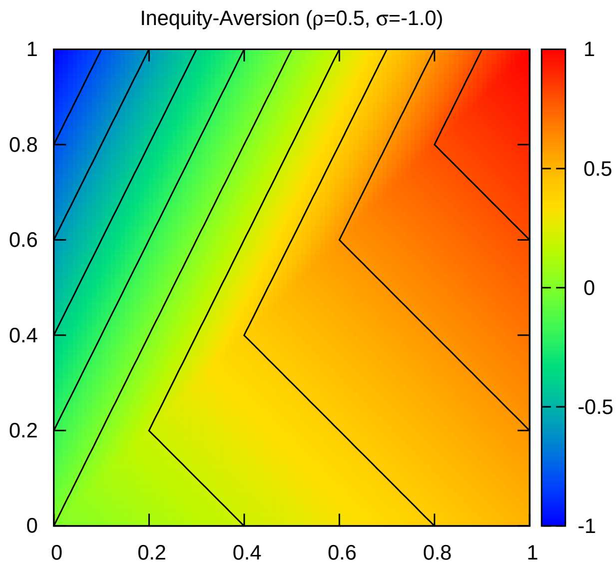

Fig. 5.2: Example of an inequity-aversion utility

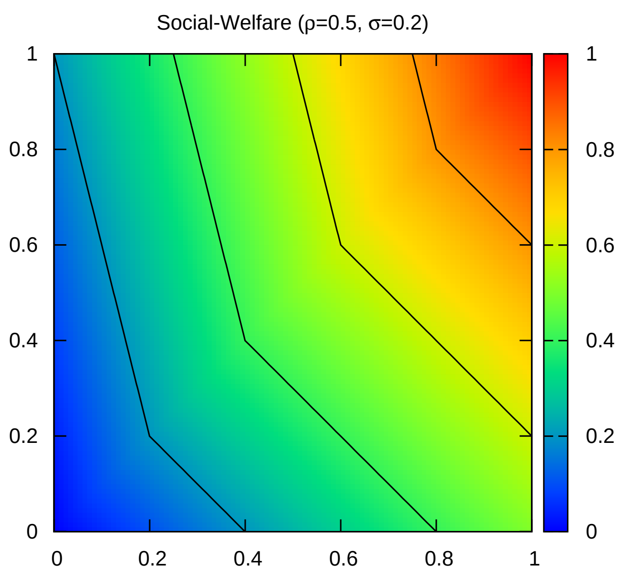

Fig. 5.3: Example of a social-welfare utility

As we have demonstrated, in the case of two subjects the inequity aversion and social-welfare utility functions coincide, but the question arises whether they are generalized to the case of many players in the same way. We will demonstrate that these two utility functions are generalized in different ways.

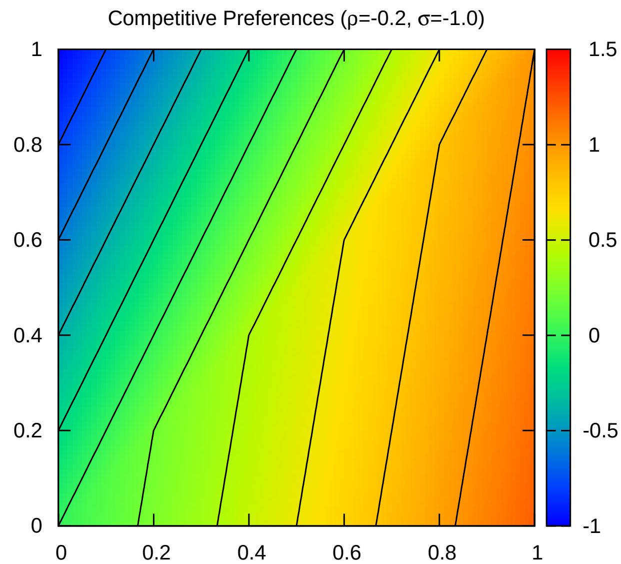

Fig. 5.4: Example of a competitive utility

Moreover, we will provide a third way to make this generalization. We also argue why we think the generalization approach that we propose provides a more adequate description of the behavior of the subjects. First, we formalize the procedure that is used to generalize the inequity aversion function. Second, we apply this procedure to the social-welfare utility function for two subjects to make it more obvious that the many-subjects inequity aversion utility functions differs from the many-subjects social-welfare function. Third, we examine the logic behind the two ways to make the generalization to the many-subjects case and present a new way to make this generalization.

It can be easily demonstrated that the many-subjects inequity aversion utility function (5.15) can be obtained from the two-subjects utility function (5.1) in the following way:

$$U_{ia}^{(n)}\left(x_1,\ldots,x_i,\ldots,x_n\right) = \frac{1}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n} U_{ia}^{(2)}\left(x_i,x_j\right) \tag{5.17}$$

Let us apply this procedure to the modified social-welfare utility function (5.3):

$$\frac{1}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n}(1-\lambda)x_i + \lambda\left[\frac{1}{2}\left(1-\delta\right)\left(x_i+x_j\right)+\delta\min\left(x_i,x_j\right)\right] =$$

$$\left(1-\lambda\right)x_i + \frac{\lambda\left(1-\delta\right)}{2}x_i + \frac{1}{n-1}\frac{\lambda\left(1-\delta\right)}{2}\sum_{\substack{j=1\\ j\neq i}}^{n}x_j + \frac{\lambda\delta}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n}\min\left(x_i,x_j\right). \tag{5.18}$$

As is evident, the structure of the above expression 5.18 is different from those of the social-welfare function written for more than two subjects (5.16), in spite of the fact that we started from the two-subjects social-welfare function (5.3). Let us consider the difference between the above expression and the many-subject social-welfare function (5.16) in more detail. The first observation is that the above utility function, which is nothing but the inequity aversion utility written in a different way, contains some terms that could be associated with the egoistic preferences, Hick optimality (cooperativeness) and the maximin utility. The first difference is that the cooperative term (the third one) in the equation 5.18 does not contain the contribution from the subject for whom the utility is given. Moreover, it is divided by the number of subjects. In other words, the above inequity aversion utility function uses the average payoff of the subjects while the social-welfare utility uses the total payoff of the subject. To make the above expression closer to the social-welfare function we will remove the $n-1$ term from the expression. In this case the second term can go under the sum of the third term and we will get the same Hick optimality terms as in the social-welfare utility function:

$$(1-\lambda)\,x_i + \lambda\left[\frac{1}{2}\,(1-\delta)\sum_{j=1}^{n} x_j + \delta \sum_{\substack{j=1 \\ j\neq i}}^{n} \min\left(x_i, x_j\right)\right]. \tag{5.19}$$

Now the expression becomes more similar to the original social welfare utility function (5.16). The 1/2 coefficient in front of the Hick optimality term is there just because we used the modified version of the social-welfare function (5.3) instead of the original one (5.2).

5.4 Alternative Generalization Procedure

The only difference between the last expression and the original social-welfare function is the maximin fairness term. In the case of the social-welfare function the fairness is calculated as the minimal payoff in the group. In the above expressions the subject compares himself with all other subjects in the group and for every comparison the fairness is calculated and is added to the total fairness. This difference demonstrates that there could be different ways to calculate the total fairness or, in other words, there could be different ways to generalize the maximin fairness from the two-subjects case to the more than-two-subjects case. We think that using the term used in the social-welfare function has a fundamental problem. We will demonstrate that with the following example. Assume that a subject needs to choose between the following two situations:

Situation #1: 50 subjects get 11 points, another 50 subjects get nine points, and one subject gets seven points.

Situation #2: 50 subjects get 12 points, another 50 subjects get eight points and one subject gets seven points.

Transition from Situation #1 to Situation #2 seems to make the distribution of points less fair since the rich subjects start to get even more and pure subjects start to get even less. However, according to the expression used in the social-welfare function the fairness of both situations is the same (it is equal to 7, the minimal payoff in the group). To resolve this problem we propose to calculate the fairness of the payoffs distributions for all possible pairs of players and sum the values up:

$$\sum_{\substack{k,l=1 \\ k \neq l}}^{n} \min\left(x_k, x_l\right). \tag{5.20}$$

Additionally, we have to decide how the weighting factor in front of this expression should depend on the number of the subjects in the group. The problem is that in the Hick optimality terms we have n summands while in the maximin that we have just introduced the number of terms is $n^2 - n$. As a result the fairness terms will dominate the cooperation term if n is large enough. To resolve this problem we propose to calculate the average fairness. For that we divide the total fairness by the number of terms under the sum $n\left(n-1\right)$. This quantity should not grow as n grows. Since the Hick optimality is proportional to n, we multiply the average fairness of the distribution by n. This way to combine the maximin fairness and Hick optimality ensures that none of these terms will dominate another one for large n. In summary, we propose to use the following utility function for the case of more than two subjects:

$$U = \left(1-\lambda\right) x_i + \lambda \left[\frac{1}{2}\left(1-\delta\right)\sum_{j=1}^{n} x_j + \frac{1}{2}\frac{\delta}{n-1}\sum_{\substack{k,l=1 \\ k \neq l}}^{n} \min\left(x_i, x_j\right)\right]. \tag{5.21}$$

For the case of two players the above utility function is the same as the inequity aversion and the social-welfare utilities functions. For the case of more than two subjects all three utilities functions are different.

5.5 The Second Type of Fairness

In the proposer-responder settings the decisions of the proposer (what option will be proposed) depends not only on the payoffs of the options but also on the payoffs of the default option [40]. By the default option we mean the option that will be implemented if the proposer does not propose anything or if the responder rejects the proposed option. In particular we can assume that the subjects care not only about the absolute payoffs associated with the options but also about the gain in the payoff that an option provides in addition to the default score. In other words, we assume that the subjects perceive the payoffs of the default option as something that they already have since proposer and responder can always get the default option, if they want, independently of what the actions of the co-player are. As a result we could assume that subjects judge all other options by the amount of points that these options give in addition to what the subjects already have from the default option. We will call this amount gqain from the option. If we introduce gain into consideration, we can assume that it is treated the same way as the absolute payoff of the option. In other words, we can assume that subjects might want to maximize their own gain or the total gain of all the subjects. However, utilities of this kind do not add anything new to the above considered utilities since a maximization o the gain is equivalent to the maximization of the absolute payoff. The same is valid for the total gain and total absolute payoff. In contrast, the maximum fairness of the gain is not identical to the maximin fairness calculated for the absolute score. In this way, the extended social-welfare utility function taking into account gains from the options can be written in the following way:

$$U_{4\omega}(p,r) = p + \omega_c(p+r) + \omega_f \min(p,r) + \omega_g \min(p-p_0, r-r0), \tag{5.22}$$

where ω_c, ω_f, and ω_g are weighting factors that represent importance of cooperation and different kinds of fairness to the given player, respectively. The first term p captures the egoistic preferences. It has no coefficient (weighting factor) preceding it because the utility function is invariant with respect to a positive scaling factor and, as a result, we can always choose such a scaling factor that makes the coefficient preceding the egoistic term equal to zero. This normalization is convenient since in this case the importance of other factors will be given relative to the importance of the player's own benefit.

5.6 Removal of Redundancy from Utility Function

We have just introduced a generalization of the social-welfare utility function that captures two kinds of fairness. Let us consider the question of the analogous generalization of the inequity-aversion function. The following expressions would be a straightforward way to make the generalization:

$$\begin{aligned} U_{gfs}(p,r) = {} & p - \alpha \max(r-p,0) - \beta \max(p-r,0) \\ & -\alpha^* \max(\Delta r - \Delta p, 0) - \beta^* \max(\Delta p - \Delta r, 0), \end{aligned} \tag{5.23}$$

where $\Delta p = p - p_0$ and $\Delta r = r - r_0$. We will call this utility function the generalized inequity aversion utility function.

In the case of the original inequity aversion utility function (5.1), the payoff space is split into two sub-spaces depending on who gets more points, proposer or responder. In each sub-space the utility function is just a linear function combining payoffs of the proposer and responder. In the general case the linear functions from different regions differ from each other. In the case of the generalized utility aversion function the payoff space is split into three regions by two lines. The first line is the same as in the case of the original inequity aversion utility function: $r = p$. The second line is parallel to the first one and goes through the default option: (p_0, r_0). The second line is given by the following equation: $r = r_0 + (p - p_0)$. In every region the generalized utility function is given by a linear function. Therefore we need to use only three parameters to describe the generalized inequity aversion utility function (5.45). However, as we can see in the equation (5.45), there are four parameters. To remove the redundancy from the formula, let us consider the linear functions representing the utility function in different regions. There are four different cases: 1) $p > r$ and $\Delta p > \Delta r$, 2) $p > r$ and $\Delta p < \Delta r$, 3) $p < r$ and $\Delta p > \Delta r$, 4) $p < r$ and $\Delta p < \Delta r$. For these cases the utility function (5.45) reduces to:

$$U_{gia}(p,r) = p - (\beta + \beta^*)(p - r) - \beta^*(r_0 - p_0) \quad if \quad p > r \wedge \Delta p > \Delta r, \tag{5.24}$$
$$U_{gia}(p,r) = p - (\beta - \alpha^*)(p - r) - \alpha^*(p_0 - r_0) \quad if \quad p > r \wedge \Delta p < \Delta r, \tag{5.25}$$
$$U_{gia}(p,r) = p - (-\alpha + \beta^*)(p - r) - \beta^*(r_0 - p_0) \quad if \quad p < r \wedge \Delta p > \Delta r, \tag{5.26}$$
$$U_{gia}(p,r) = p - (-\alpha - \alpha^*)(p - r) - \alpha^*(p_0 - r_0) \quad if \quad p < r \wedge \Delta p < \Delta r. \tag{5.27}$$

The above set of equations can be rewritten in the following simplified form:

$$U_{gia}(p,r) = p - \alpha_{pp}(p - r) - c_{pp} \quad if \quad p > r \wedge \Delta p > \Delta r, \tag{5.28}$$
$$U_{gia}(p,r) = p - \alpha_{pr}(p - r) - c_{pr} \quad if \quad p > r \wedge \Delta p < \Delta r, \tag{5.29}$$
$$U_{gia}(p,r) = p - \alpha_{rp}(p - r) - c_{rp} \quad if \quad p < r \wedge \Delta p > \Delta r, \tag{5.30}$$
$$U_{gia}(p,r) = p - \alpha_{rr}(p - r) - c_{rr} \quad if \quad p < r \wedge \Delta p < \Delta r. \tag{5.31}$$

In the above equations the relation between the utility of the player's own benefit and benefit of the co-player is given by the coefficients α_{ij}.

$$\beta + \beta^* = \alpha_{pp}, \tag{5.32}$$
$$\beta - \alpha^* = \alpha_{pr}, \tag{5.33}$$
$$-\alpha + \beta^* = \alpha_{rp}, \tag{5.34}$$
$$-\alpha - \alpha^* = \alpha_{rr}, \tag{5.35}$$

It is easy to notice that the values of the coefficients α_{ij} are invariant with respect to the following transformation of the coefficients α, β, α^* and β^*:

$$\beta_{new} \rightarrow \beta_{old} + \gamma \tag{5.36}$$
$$\alpha_{new} \rightarrow \alpha_{old} - \gamma \tag{5.37}$$
$$\beta^*_{new} \rightarrow \beta^*_{old} - \gamma \tag{5.38}$$
$$\alpha^*_{new} \rightarrow \alpha^*_{old} + \gamma \tag{5.39}$$

So, to remove the ambiguity from the equations (*i.e.*, to fix the γ) we can apply the following constraint on the coefficients:

$$\beta - \alpha = \beta^* - \alpha^* \tag{5.40}$$

If we have an initial set of the coefficients α_o, β_o, α^*_o and β^*_o, we can use transformation (5.32-5.35) to get the new values for the coefficients α_n, β_n, α^*_n and β^*_n. The parameter γ can be found in the following way:

$$\beta_n - \alpha_n = \beta^*_n - \alpha^*_n \tag{5.41}$$
$$(\beta_o + \gamma) - (\alpha_o - \gamma) = (\beta^*_o - \gamma) - (\alpha^*_o + \gamma) \tag{5.42}$$
$$(\beta_o - \alpha_o) + 2\gamma = (\beta^*_o - \alpha^*_o) - 2\gamma \tag{5.43}$$
$$\gamma = \frac{1}{4}[(\beta^*_o - \alpha^*_o) - (\beta_o - \alpha_o)] \tag{5.44}$$

For the next step we transform the expression (5.45) to explicitly utilize the above introduced relation between the utility parameters (5.40). First, we will use the following formula $\max(x,0) = -\min(-x,0)$.

$$\begin{aligned} U^g_{fs}(p,r) &= p + \alpha \min(p-r,0) - \beta \max(p-r,0) \\ &+\alpha^* \min(\Delta p - \Delta r, 0) - \beta^* \max(\Delta p - \Delta r, 0). \end{aligned} \tag{5.45}$$

Second, we utilize the relation between the utility parameters to decrease their number from four to three:

$$\begin{aligned} U_{3r}(p,r) &= p - \\ &- (\omega+f)\max(p-r,0) - (\omega-f)\min(p-r,0) - \\ &- (\omega+g)\max(\Delta p-\Delta r,0) - (\omega-g)\min(\Delta p-\Delta r,0). \end{aligned} \tag{5.46}$$

We will denote the utility function of this form as U_{3r} to indicate the fact that it splits the payoff space into three regions in which the utility function is a linear function of the two parameters (p and r). The parameter f is responsible for the sensitivity of the subject to the inequity of the final benefit. If $f = 0$, then the terms containing f make the same contribution to the $p > r$ and $p < r$ regions. In other words, for a subject with $f = 0$ it does not matter what is larger his/her benefit (p) or benefit of his/her co-player (r).

5.7 Relation between Generalized Social Welfare and Inequity Aversion

Let us now show that the utility function constructed as a linear combination of four strategies (5.22) is identical to the generalized inequity aversion utility function (5.47). To find the relation between the two utility functions we will separately consider four different cases: 1) $p > r$ and $\Delta p > \Delta r$, 2) $p > r$ and $\Delta p < \Delta r$, 3) $p < r$ and $\Delta p > \Delta r$, 4) $p < r$ and $\Delta p < \Delta r$. For the first case ($p > r$ and $\Delta p > \Delta r$) we have:

$$U_{4\omega} = p(1+\omega_c) + r(\omega_c+\omega_f+\omega_g) - \omega_g r_0, \tag{5.47}$$
$$U_{3r} = p(1-2\omega-f-g) + r(2\omega+f+g) + (\omega+g)(r_0-p_0) \tag{5.48}$$

For the second case ($p > r$ and $\Delta p < \Delta r$) we have:

$$U_{4\omega} = p(1+\omega_c+\omega_g) + r(\omega_c+\omega_f) - \omega_g p_0, \tag{5.49}$$
$$U_{3r} = p(1-2\omega-f+g) + r(2\omega+f-g) + (\omega-g)(r_0-p_0) \tag{5.50}$$

For the third case ($p < r$ and $\Delta p > \Delta r$) we have:

$$U_{4\omega} = p(1+\omega_c+\omega_f) + r(\omega_c+\omega_g) - \omega_g r_0, \tag{5.51}$$
$$U_{3r} = p(1-2\omega+f-g) + r(2\omega-f+g) + (\omega+g)(r_0-p_0) \tag{5.52}$$

For the fourth ($p < r$ and $\Delta p < \Delta r$) case we have:

$$U_{4\omega} = p(1+\omega_c+\omega_f+\omega_g) + r(\omega_c) - \omega_g p_0, \tag{5.53}$$
$$U_{3r} = p(1-2\omega+f+g) + r(2\omega-f-g) + (\omega-g)(r_0-p_0) \tag{5.54}$$

By comparing the oefficients preceding p and r in $U_{4\omega}$ and U_{3r} we will get the following set of 8 equations:

$$\alpha(1+\omega_c) = 1-2\omega-f-g \tag{5.55}$$
$$\alpha(1+\omega_c+\omega_g) = 1-2\omega-f+g \tag{5.56}$$
$$\alpha(1+\omega_c+\omega_f) = 1-2\omega+f-g \tag{5.57}$$
$$\alpha(1+\omega_c+\omega_f+\omega_g) = 1-2\omega+f+g \tag{5.58}$$

and

$$\alpha(\omega_c+\omega_f+\omega_g) = 2\omega+f+g \tag{5.59}$$
$$\alpha(\omega_c+\omega_f) = 2\omega+f-g \tag{5.60}$$
$$\alpha(\omega_c+\omega_g) = 2\omega-f+g \tag{5.61}$$
$$\alpha(\omega_c) = 2\omega-f-g \tag{5.62}$$
$$\tag{5.63}$$

We have added a coefficient α to address the fact that the two utility functions can use different normalizations. If we add the first equation from the first subset of equations to the first equation from the second subset we get the following equation:

$$\alpha(1+2\omega_c+\omega_f+\omega_g) = 1 \tag{5.64}$$

The same equation can be obtained if we add the second, third or fourth equations from the two above subsystems. From the last equation we can easily get the scaling factor for the $U_{4\omega}$ utility based on its parameters.

$$\alpha = \frac{1}{1+2\omega_c+\omega_f+\omega_g} \tag{5.65}$$

After the scaling with the factor α the $U_{4\omega}$ will coincide with the U_{3r}:

$$\alpha U_{4\omega} = U_{3r}. \tag{5.66}$$

From the first equation of the first subsystem it is easy to get ω_c. After ω_c is found we can use the second equation to find ω_g, and from the third equation we get ω_f. In this way we get the following solution:

$$\omega_c = \frac{1}{\alpha}(1-\alpha-f-g-2\omega) \tag{5.67}$$
$$\omega_g = \frac{2g}{\alpha} \tag{5.68}$$
$$\omega_f = \frac{2f}{\alpha} \tag{5.69}$$

5.8 Fair Gain and More than Two Subjects

The above proposed utility function models fairness with respect to the final score. We would like to generalize the above function to include the second kind of fairness - the fairness with respect to the gain. To do so we could just add one more term to the utility function:

$$\sum_{\substack{k,l=1\\k\neq l}}^{n} \min\left(x_i - x_i^d, x_j - x_j^d\right), \tag{5.70}$$

where x_i^d denotes the default score of player i. However, as we have seen before, in this way we will introduce ambiguity into the utility function. In other words, different values of the utility parameters could give the same utility function. To resolve this problem we should take the two-subjects utility function with the removed ambiguity (5.47) and generalize it to the case of more-than-two players. To do so we have to formalize the generalization procedure. In other words, we have to find the procedure that transforms the modified social-welfare utility (5.3) to the desired many-subject utility functions (5.21). After we find this procedure, we can apply it to the two-subjects utility with removed ambiguity and, in this way, we should obtain the many-subject utility without ambiguity.

Let us first take the two-subject utility (5.3) and sum it up for all possible pairs of subjects and then divide by the number of the considered pairs:

$$\frac{1}{n\,(n-1)} \sum_{\substack{k,l=1\\k\neq l}}^{n} \left\{(1-\lambda)x_k + \lambda\left[\frac{1}{2}\,(1-\delta)\,(x_k+x_l) + \delta\min\left(x_k, x_l\right)\right]\right\} \tag{5.71}$$

The above equation can be transformed to the following form:

$$(1-\lambda)\,x_i + \lambda\left[(1-\delta)\,\frac{1}{n}\sum_{j=1}^{n} x_j + \frac{\delta}{n\,(n-1)}\sum_{\substack{k,l=1\\k\neq l}}^{n} \min\left(x_k, x_l\right)\right] \tag{5.72}$$

If we compare the above equation (5.72) and the earlier proposed equation (5.21), we can see that the equation (5.21) can be obtained from the equation (5.72) if the following substitution $\lambda \to \lambda n/2$ before the social term is used. In other words, the generalization of the two-subject case (5.3) can be done if we replace λ by $n\lambda/2$ and average this two-subjects utility for all possible pairs of subjects. Now we can apply this procedure to the two-subjects utility (5.47) that incorporates the two kinds of fairness and in which the ambiguity in the parameters is removed.

$$\begin{aligned} U_{3r}(p,r) = p &- \frac{1}{2\,(n-1)} \sum_{\substack{k,l=1\\k\neq l}}^{n} \left[(\omega+f)\max(p-r,0) + (\omega-f)\min(p-r,0)\right] \\ &- \frac{1}{2\,(n-1)} \sum_{\substack{k,l=1\\k\neq l}}^{n} \left[(\omega+g)\max(\Delta p-\Delta r,0) + (\omega-g)\min(\Delta p-\Delta r,0)\right] \end{aligned} \tag{5.73}$$

5.9 Summary of the Derivation

We have compared the inequity-aversion and social-welfare utility functions. We have demonstrated that, despite the fact that the two considered utility functions are identical for the case of two subjects, their generalizations to the case of more-than-two subjects are different. The generalization procedures have been compared and analyzed. As a result, we have proposed a new generalization procedure that is different from the generalization procedures applied to the inequity-aversion and social-welfare utility functions. The proposed way to generate utility functions for more-than-two subjects provides several advantages. First, the fairness of the payoff distributions is calculated by consideration of all possible pairs of subjects. This is different from the calculation of the fairness prescribed by the inequity-aversion functions in which only pairs containing the decision-making subjects are considered. Second, the importance of the social contribution to the utility functions, as compared to the egoistic contribution, grows as the size of the group grows. The inequity-aversion utility does not have this property. Third, the utility proposed for the case of more-than-two subjects becomes less sensitive to the payoff of a single subject as the size of the group grows. This is different from the social-welfare utility which could be very sensitive to the payoff of one player even for huge groups. Finally, we have proposed an additional maximin fairness term to the utility function to capture the fact that proposers can behave differently depending on how many points the default option gives to the proposer and responder. In summary, we have proposed a many-subjects utility function that can explain egoistic, cooperative and fair behavior of different kinds in the proposer-responder setting.

6. HORIZON EFFECT

In this chapter we extend the utility-based model, introduced in the previous chapter, with a model which treats the inability of players to find all the options available to them in the game. The need for an additional model, which we will call a model of noticing, arose from the fact that for many players we were not able to find utility parameters that would agree with all the decisions made by the given player. In the beginning of this chapter we describe our effort to understand this fact. In particular we have created a hypothesis that in some cases players are not able (or are not willing) to calculate all the options in the game because of the combinatorial complexity of the game. To verify this hypothesis we have introduced three possible sources of the combinatorial complexity of the CT game and numerical measures for them. These three measures of complexity can be used to describe the combinatorial complexity of every option in the CT game. For all three measures we have demonstrated that the combinatorial complexity associated with them reduces the probability of an option to be proposed (noticed). In this way we have proved that some options can be unnoticed by players because of their combinatorial complexity. In other words, we have explained why in many cases it is impossible to find utility parameters that would be consistent with all the decisions made by a player.

In the second part of this chapter we try to define a measure of inconsistency between a given set of utility parameters and a given set of decisions. The main role of this measure is to be used in a minimization procedure over the utility parameters. By this minimization procedure we can find a set of utility parameters that is the most consistent with the decisions of a given player. We demonstrate that there are different ways to define such a measure and that some of the definitions lead to a systematic underestimation of the cooperative component of the utility function. We try to find a reason of this underestimation and to reduce it by construction of a better measure. Finally, we demonstrate that a definition of any probabilistic model of noticing naturally provides us with a measure of inconsistency and even the measures that came from the simplest models of noticing perform better than any constructed measure. At the end of this chapter we discuss in what direction the probabilistic models of noticing can be generalized and improved and how parameters of these models can be used to monitor cognitive fatigue. We also briefly mention other effects which can contribute to the disagreement of the observed decisions with the utility model in addition to the effect of not noticing of options.

6.1 Effect of Combinatorial Complexity

Within our approximation we assume that players make their decisions based on some fixed utility function of the above introduced form (5.47). In more detail, we assume that every player uses his/her utility function to calculate utility of every option based on the two payoffs associated with this option. Then the option with the highest utility is proposed. Our goal is to find utility parameters that could explain decisions of a given player. For this purpose we need to define a procedure that maps decisions of a player into utility parameters.

In most of the cases a fixed set of utility parameters uniquely determines decisions in the proposal phase (*i.e.*, options that maximize the utility function). In other words, if we know the utility parameters modeling behavior of a given player, we should be able to predict this player's decisions. This will not be possible only if several options have the same utility. However, the opposite statement is not correct. A given decision of a player determines a region (not just a point) in the 3D space of the utility parameters, which contains the utility parameters leading to the observed decision. In other words, every decision of a player made in a proposal phase should generate a region in the space of utility parameters. As a result, a set of decisions from different games should produce a set of regions, each of which contains a point representing the utility parameters associated with the considered player. The overlap between all the regions, corresponding to different decisions of the player, should contain the utility parameters of the player. The size of the overlap should decrease as the number of decisions (regions) grows.

Analysis of the data from our web-based experiment and from the Mars-500 experiment have shown that there are two contradictions with the above described simple model. First, we have found that some decisions cannot be explained by any set of the utility parameters; for these decisions we could not find a utility function that is maximized by the proposed options. Second, we have noticed that sometimes utility regions, corresponding to the decisions in different games, are not overlapping. That is, for every decision we were able to find utility parameters that would explain the given decision, but there are no utility parameters that could explain all the decisions at the same time.

There can be several reasons for the disagreement of the data with the above described simple model. First, it can be that utility parameters of the players are not constant. For example, the utility parameters can be dependent on time or on who the opponent is. In other words, decisions of a player in different games can be made by different utility parameters. This effect can explain why for some games we cannot find a single set of utility parameters that could explain decisions in all the games. However, the assumption of changing utility parameters cannot explain why for some games it is impossible to find utility parameters that would explain a single decision made in these games. To explain this property of the decisions we could assume that the form of the utility that we use is not good enough to capture these decisions. However, the options that could not be explained by the introduced utility are located in the middle of the cloud of available options and, as a result, they also could not be explained by any other utility of a reasonable form. A more realistic assumption is that the players are not able to see all the available options in the proposal phase because of the combinatorial complexity of the game. To verify this assumption we are going to identify sources of combinatorial complexity and check if the options that are less hidden by the combinatorial complexity of the game are more likely to be proposed. We have identified three characteristics of the decisions that can potentially correlate with the combinatorial complexity of the options. Then we check if the sets of noticed and not noticed options are statistically different in terms of the three introduced characteristics of the options.

First, every option (payoff allocation) can be obtained by one or more exchanges of chips. We have assumed that it is easier to notice an option that is represented by many exchanges, since an option will be noticed if at least one of the exchanges associated with the option is noticed.

Second, every exchange of chips can be characterized by its size. The size of an exchange is defined as the number of chips that are involved in the exchange. For example, if a player proposes three green chips and asks in return for two blue chips, the size of the exchange is equal to five. We assume that exchanges of smaller sizes are more likely to be considered and, therefore, the corresponding options are more likely to be proposed. Since, in general cases, an option can be obtained by different exchanges, we have characterized every option by the size of the minimal exchange associated with the given option.

Third, every exchange of chips can be characterized by the number of trajectories (moves on the board) that can be done by the proposer and responder if the given exchange is implemented. Accordingly, to evaluate payoffs associated with an exchange the proposer needs to find a trajectory that maximizes his/her payoff and a trajectory that maximizes payoff of the responder. We assume that it is harder to find an optimal trajectory if there are a lot of possible trajectories. So, we can characterize every option by the total number of the trajectories corresponding to the minimal exchange of the chips associated with the given option. We assume that the larger this number is, the less likely it is that the option will be proposed.

To summarize, we have introduced three characteristics that describe the combinatorial complexity of the options: (1) number of exchanges associated with the option, (2) size of the minimal exchange, and (3) number of trajectories corresponding to the minimal exchange. The first parameter is expected to increase the probability of the option being proposed while the other two parameters are expected to decrease this probability.

To verify our hypotheses we used decisions made in seven teams (21 players) who played the largest number of games within the web-based experiment before dropping out. All payoff options were separated into three classes. The first class contains options that were proposed by the players (*i.e.*, noticed options). The second class contains options that have utilities higher than the utility of the proposed option (*i.e.*, unnoticed options). We assume that these options are unnoticed because they have utilities that are larger than the utility of the proposed option and, as a result, the user would rather propose one of these options if he/she is aware that this option exists. All other options go to the third

Parameter	Noticed Options	Unnoticed Options
Number of Exchanges	2.28	1.83
Size of the Minimal Exchange	2.30	3.24
Number of Trajectories	25.12	30.38

Tab. 6.1: Averaged values of the three complexity parameters for the noticed and unnoticed sets of options

class (options with undefined status). We cannot say if the options from the third class are noticed or unnoticed because these options will not be proposed independently of whether they are noticed or not by the player.

From the decisions collected during the web-based experiment we got 405 noticed and 2,123 unnoticed options. Every option in both groups was characterized by the three above introduced parameters. For the two considered groups of the options (noticed and unnoticed) we have calculated the average number of these introduced parameters. The values of the parameters are summarized in table 6.1. The values in this table show the following trends. We can see that the average number of the exchanges associated with the noticed (proposed) options is larger than the same property calculated for the unnoticed options (2.281 and 1.827, respectively). This trend supports our assumption that an option is more likely to be proposed if there are more chips exchanges that give this option. The relation between the average values of the size of the minimal exchange calculated for the two classes of options support our second hypothesis. As we can see in table 6.1 the average size of the minimal exchanges calculated for the set of noticed options is smaller than the corresponded value calculated for the set of unnoticed options (2.296 and 3.239, respectively). In other words, we can say that players tend to notice options associated with smaller exchanges of chips. Finally, the average number of the trajectories associated with the minimal exchange corresponding to the options also shows the expected trend. As we can see the players tend to notice exchanges with a smaller number of trajectories associated with them. The average number of the trajectories of the minimal exchanges for the noticed and unnoticed options are 25.123 and 30.382, respectively.

If we assume that noticed and unnoticed options are statistically indistinguishable in terms of the three parameters described above, the probability that we will observe the correct trend for all three parameters just by chance is quite high (it is equal to 1/8). To make a more solid conclusion we have compared not only the average values of the complexity parameters but also their distributions, as shown in figures 6.1, 6.2 and 6.3. As we can see in figure 6.1 the portion of the options represented by 3 and more exchanges is larger in the set of the noticed options. This supports our assumption that an option is more likely to be noticed if it can be obtained by a larger number of chips exchanges. As we can see in figure 6.2 the distribution of the sizes of the minimal exchanges calculated for the noticed options (red line) dominates the corresponding distribution calculated for the unnoticed options (blue line) in the region of the small

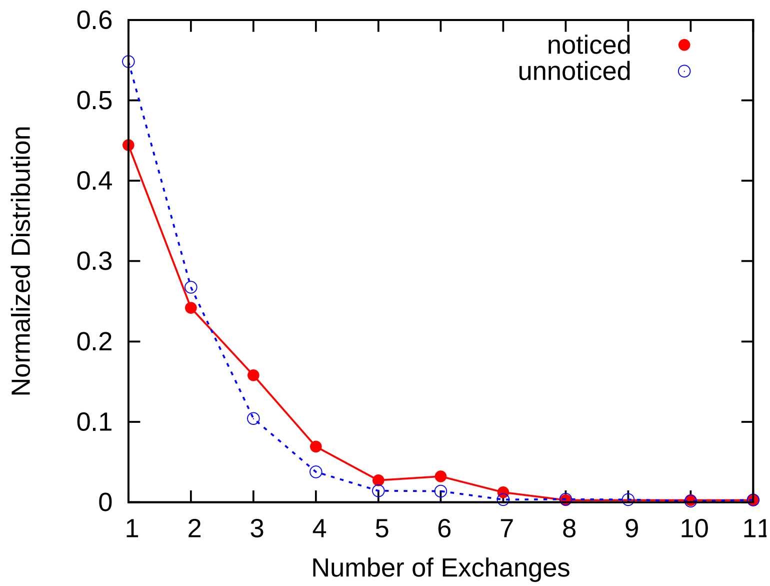

Fig. 6.1: Distribution of number of exchanges associated with the options from the groups of noticed and unnoticed payoffs options

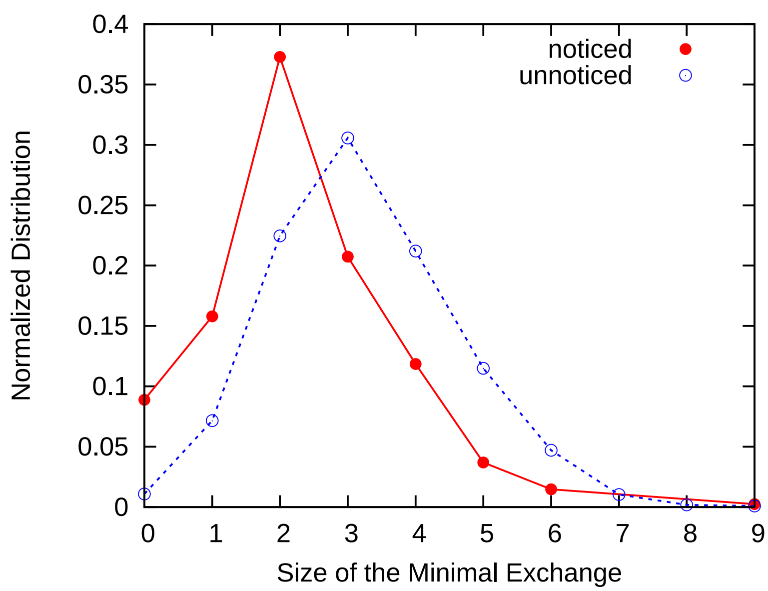

Fig. 6.2: Distributions of the sizes of the minimal exchanges for the groups of noticed and unnoticed payoffs options

values (from 0 to 2). From that we can conclude that players tend to propose

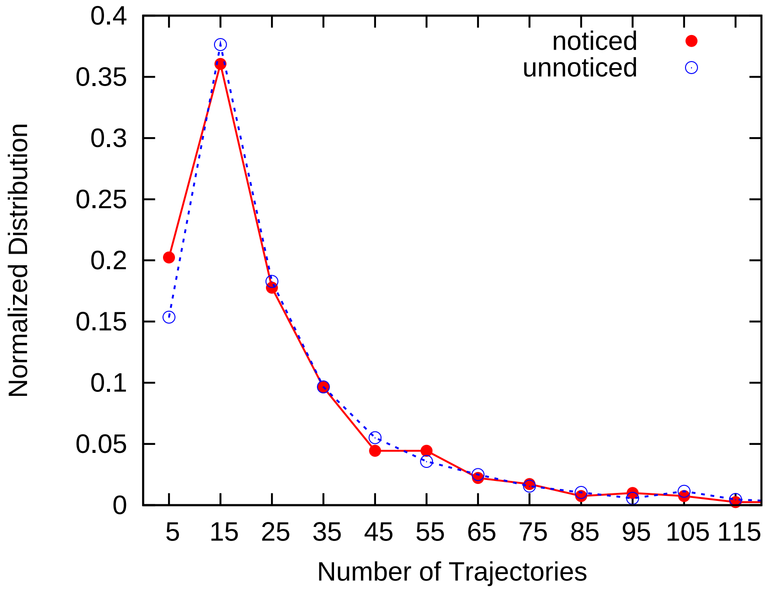

Fig. 6.3: Distributions of the total number of trajectories which are possible with minimal chips exchange associated with the options from the noticed and unnoticed groups

simple exchanges and an exchange with a higher utility can have smaller probability to be proposed if it is more complex to identify it. The distributions of the number of trajectories corresponding to the minimal chips exchange (figure 6.3) looks not as convincing as the distributions for the other two complexity parameters. We see that options corresponding to a small number of trajectories (around five) are more frequent among the noticed options and options with the larger number of the trajectories (around 15 and 25) are more frequent for the unnoticed options. However, the difference between the distributions is so small that it is not clear if the observed trends are just noise.

To make a solid conclusion about the validity of our hypothesis, stating that the three introduced characteristics of the options influence the probability of noticing these options, we need to prove that the difference between the average values of the complexity parameters is statistically significant. The null hypothesis is that the two sets of options (noticed and unnoticed) are statistically indistinguishable in terms of the three complexity parameters described above and the observed difference between the average values of these parameters is just noise. To calculate the p-value of the null hypothesis we have mixed the two original sets of options, shuffled the combined set and then re-split it into two new subsets of the same sizes as the two original sets. For every generated subset we have calculated the average value of a given complexity parameter and then the absolute value of the difference between the two average values was calculated. This procedure was repeated 10000 times and it was checked in how many cases the absolute difference between the two average values was as big as, or even larger, than the difference between the original two average values.

By the above described procedure we have shown that difference between the sets of noticed and unnoticed options in terms of the number of exchanges and size of the minimal exchanges has high statistical significance. In all $10,000$ tests the difference between the two randomly generated subsets was always smaller than the difference between the two original sets in terms of these two parameters. As a consequence, we can conclude that the first two complexity parameters do have an influence on the probability of the options to be proposed. In the case of the third complexity parameter (number of trajectories) the p-value was not as small as in the case of other two parameters but still quite small; it was found to be equal to 0.026. So, with a high confidence we can say that the number of trajectories also has an effect on the probability of the options to be proposed.

6.2 Measures of Inconsistency

As discussed in the previous chapter, in a general case it is impossible to find a single set of utility parameters that would be in perfect agreement with all the decisions made by a given player. Accordingly, we need to search for utility parameters that minimize the disagreement with the given set of decisions. To do so we need to define a measure of disagreement between the utility parameters and the given set of decisions. There are different ways to measure this disagreement. Since we get the utility parameters as a result of a procedure that minimizes a given measure of disagreement, the calculated utility parameters depend on the measures of disagreement that were used. It is therefore important to examine different measures of disagreement to determine which one is better suited for the calculation of the utility parameters.

The simplest way to define the quality of the utility parameters is to make it equal to the average number of options that have higher utility than the utility of the option proposed by the given player. This measure can be expressed in the following way:

$$L = \frac{1}{N_g} \sum_{g=1}^{N_g} \sum_{i=1}^{N_o(g)} \theta(u_i^g - u_p^g), \tag{6.1}$$

where N_g is the total number of the games played by a given player, $N_o(g)$ is the number of options in the game g, u_i^g is the utility of the option i in the game g and u_p^g is the utility of the options proposed in the game g. The function θ is the step function which is equal to 0 and 1 for negative and positive arguments, respectively. In the ideal case of a player who has a fixed utility and is always able to find the option maximizing his/her utility, it is possible to find such utility parameters that make the measure 6.1 equal to zero. In the real cases we usually cannot find such utility parameters. So, we just try to minimize the considered measure of the inconsistency between the decisions and utility parameters.

The disadvantage of the measure 6.1 is that it is not a smooth function of the utility parameters, because it is always equal to an integer number divided by a constant (the number of games played by the given player). As a result, if we start to shift the utility parameters smoothly from a given point in a given direction then, untill a certain value of the shift, we have no variation of the measure and then, at some point, we have a jump of the measure. Because of this property of the measure it is not a convenient function for an optimization procedure. During an optimization procedure, small variations of the utility parameters around current values do not give information about the direction in which the utility parameters should be changed.

To resolve this problem we have modified the measure in the following way:

$$L = \frac{1}{N_g} \sum_{g=1}^{N_g} \sum_{i=1}^{N_o(g)} (u_i^g - u_p^g) \cdot \theta(u_i^g - u_p^g). \tag{6.2}$$

The main idea behind this definition is as follows: If the utility of a considered option is larger than the utility of the proposed option, then its contribution to the measure of disagreement is equal to the difference between the utilities of the considered and proposed options (and not one, as in the previous case). We will call this measure "error level".

The error level has been used to calculate the utility parameters for 21 players from seven teams. Two of these teams participated in the Mars-500 experiment and the other five teams are the teams that played the largest number of games in the web-based experiment. For every player we have run a procedure that minimizes the error level as a function of the three utility parameters. For more detail about the minimization procedure see chapter 11.4 in the Appendix.

To check the quality of the found utility parameters we have used them to generate decisions in the same games that were played by the considered players. These decision have been used to calculate the angle of benefit, defined in chapter 3.1. The angles of benefit, in turn, have been used to calculate the populations of the three types of the decisions ("ask for help", "mutually beneficial" and "propose help"). The populations of the decisions of different types, calculated in this way, have been compared with the corresponding populations of the decisions made by the considered player. By this comparison we found that the utility parameters calculated by the minimization of the error level lead to a significant overestimation of the portion of the mutually beneficial decisions and underestimation of the "helpful" decisions. The real portion of the mutually beneficial decisions is about 36.71% (see the R.D. column of table 6.2), while the utility parameters calculated with the error level give 60.82 as the value of this portion (see the E.L. column of the table). The real portion of the "ask-for-help" and propose-help decisions is 27.40 and 35.89, respectively. The simulated portions for these two types of the decisions are much smaller (16.16 and 23.01, respectively). The total difference between the real populations and the simulated ones is equal to 48.22 (see the last row of the table). These results show that use of some measures of disagreement between a set of

Property	R. D.	E. L.	P. D.	U. D.	S. H. M. $r = 1$	S. H. M. $r = 2$
Ask for Help	27.40	16.16	17.13	21.92	29.32	39.39
Mutually Beneficial	36.71	60.82	58.56	49.86	38.36	34.09
Propose Help	35.89	23.01	24.31	28.22	32.33	26.51
Total Difference	0.0	48.22	43.70	26.30	7.12	22.72

Tab. 6.2: Real populations of the decisions of the three different types and the populations corresponding to the utilities parameters obtained with the different measures of the disagreement

utility parameters and a set of decisions could produce utility parameters that underestimate cooperative behavior of players. To solve this problem we need to understand why we have this effect and, based on our understanding, we need to propose a new measure.

We have proposed the following explanation of the observed underestimation of cooperative behavior. In figures 6.4 and 6.5 we show the same schematic payoff spaces that form a concave shape (like the real payoff spaces used in our experiments). With these two figures we consider two opposite cases. In the

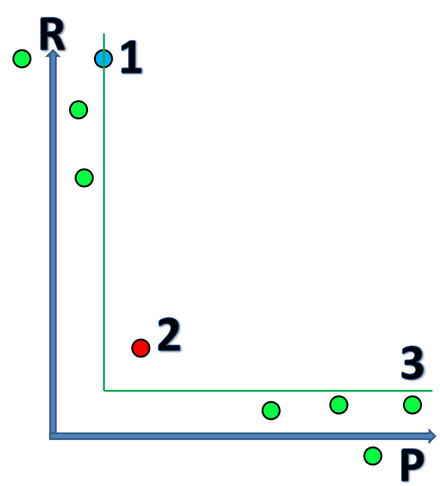

Fig. 6.4: Situation in which a cooperative proposal (the blue circle) contradicts with the fair utility (shown with the green line).

first case, shown in figure 6.4, the player chooses the most cooperative option, that is the option that maximizes the total payoff of the players. This option is shown with the blue circle (option 1). We assume that the player has a "fair" utility, given by maximin fairness. With the green line we show the part of the payoff space that has the same utility as the chosen option. This line separates the payoff space into two subspaces. The first subspace contains all the options

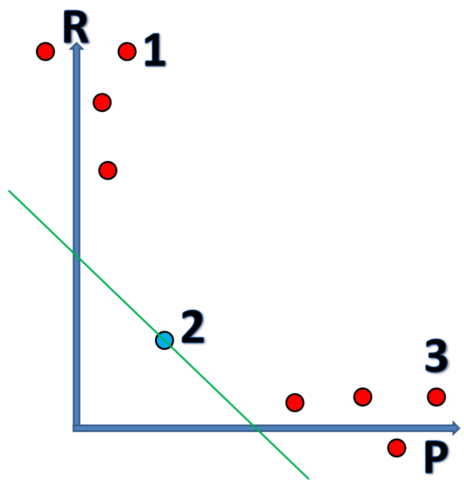

Fig. 6.5: Situation in which a fair proposal (blue circle) contradicts with the cooperative utility (shown with the green line).

whose utility is smaller than the utility of the proposed option (these options are shown with the green circles). The second subspace contains the options that have a higher utility than the utility of the proposed option. As we can see there is only one such option (option 2, shown with the red circle).

In the second case, shown in figure 6.5, we consider the opposite situation. The player chooses the fairest option (option 2) and we assume that the player has the cooperative utility. In this case we have eight options, shown with the red circles, that contradict with the assumed utility. With these two examples we can see that the cooperative utilities are discriminated more than fair utilities. Assumption of a cooperative utility under a fair proposal gives a much larger error level than assumption of a fair utility under a cooperative proposal. As a result it is less costly to assume a fair utility rather than a cooperative one. For example, if we have a hypothetical situation in which a player made one cooperative and one fair decision, the error level will be smaller if we assume that player uses a fair utility rather than cooperative one. Therefore, the minimization procedure will return a fair utility despite the fact that the player made cooperative proposals as frequently as fair ones.

To resolve the problem of the discrimination of cooperative utilities we have proposed a new measure of disagreement between the given set of utilities parameters and a given set of decisions. To calculate this measure of disagreement we use a given set of utility parameters to find the option that maximizes the utility function and then we calculate the distance between this option and the option proposed by the player. With this definition of the measure of disagreement the treatment of the fair and cooperative options becomes symmetric. For example, in the case of the cooperative proposal and the fair utility (figure 6.4), 1 is the proposed option and 2 is the option that maximizes the assumed utility function. In this case the measure of disagreement is equal to the distance between these two points in the payoff space. In the opposite case, where the fairest option is proposed and the cooperative utility is assumed (see figure 6.5), the measure of disagreement is also given by the distance between points 1 and 2 (because option 2 is the proposed option and option 1 is the option that maximizes the assumed utility). As we can see, the new definition of the measure of inconsistency removes the above considered discrimination of the cooperative utilities.

Hereafter we will call this measure "payoff distance". The formal definition of this measure is given by the following expression:

$$L = \frac{1}{N_g} \sum_{g=1}^{N_g} \sqrt{\left(p_p^g - p_m^g\right)^2 + \left(r_p^g - r_m^g\right)^2}, \tag{6.3}$$

where p^g and r^g are the payoff of the proposer and responder in the game g, respectively. The lower indexes p and m are used to indicate the proposed option and the option that maximizes the assumed utility, respectively.

If we use the payoff distance instead of the error level as the measure of the disagreement level, we get a better agreement between the real decisions in terms of the population of different kinds decisions. The improvement is observed for all three kinds of decisions. The portion of the decisions in which players "ask for help" and "propose help" grows from 16.16% to 17.13% and from 23.01% to 24.31%, respectively. This shows a decrease of the underestimation of the portion of the helpful decisions. The portion of the "mutually beneficial" decisions decreases from 60.82% to 58.56%. Therefore, we also have a decrease of the overestimation of the mutually beneficial (fair) proposals. The total improvement of the results is given by the numbers in the last row of table 6.2. The transition from the error level to the payoff distance decreases the total disagreement with the real population from 48.22% to 43.70%. However, if we compare the values form the P.D. (payoff distance) column with the values from the R.D. (real decisions) column, we can see that we still have an overestimation of the portion of the mutually beneficial decisions and underestimation of the portion of the helpful decisions. As a result, the use of the new measure reduced the systematic deviation from the real proportions but did not remove it. It means that we still have discrimination of the cooperative proposals.

We assumed that this discrimination is conditioned by the fact that some cooperative decisions might be very close in terms of the utility but very distant in terms of the payoff distance. For example, the cooperative utility of options 1 and 3 can be very close but the distance between these points in the payoff space is quite large. Let us consider a player with a cooperative utility. This player is expected to choose option 1, which maximizes the cooperative utility. However, it can easily happen that the considered player chooses option 3 because its utility is very close to the utility of option 1. If we then use the payoff distance as the measure of the disagreement, we get a larger value of the disagreement between the choice of the player and the assumption of the cooperative utility (despite of the fact that the player has the cooperative utility). This is another mechanism of the discrimination of the cooperative utility. This discrimination mechanism works only for cooperative utilities and not for the fair ones because the options that maximize the fair utility are close to each other in the payoff space. To prevent the above describing discrimination of the cooperative utilities we have proposed another measure of disagreement. We propose to measure distance between the points not by their distance in the payoff space but by the difference between their utilities. This measure is given by the following expression:

$$L = \frac{1}{N_g} \sum_{g=1}^{N_g} \left(u_m^g - u_p^g \right) , \tag{6.4}$$

where u denotes the utility of the options and the lower indexes p and m are used, as before, to indicate the proposed option and the option that maximizes the considered utility, respectively. We will call this measure of disagreement "utility distance". If we switch from the payoff distance to the utility distance, we have an improvement for all three populations, like in the case of the switch from the error level to the payoff distance [see the U.D. (utility distance) column of table 6.2]. Also, like in the case of the other measures we have an underestimation of the portion of the cooperative proposals and an overestimation of the portion of the fair proposals. However, in the case of the utility distance, the disagreement with the populations corresponding to the real decisions is significantly reduced. The total disagreement in case of the utility distance is only 26.30, which is quite small when compared to the disagreements corresponding to the two earlier introduced measures (48.22 and 43.70).

In this chapter we have demonstrated that we need to define a measure of disagreement to calculate a set of utility parameters corresponding to a given set of decisions made by a player. Moreover, we have shown that a correct choice of the measure of disagreement is very important since for some measures we can have a systematic underestimation of the cooperative preferences of the players. We have also demonstrated two mechanisms that can lead to the underestimation and based on that we have proposed two measures that reduce the underestimation. By an appropriate construction of the measure we could reduce the effect of the discrimination of the cooperative decisions but could not completely remove it. In the next chapter we describe an alternative approach to the construction the measures of disagreement (a model based approach). We will demonstrate that with the new approach we can reduce the discrimination effect in a more natural and efficient way, which will lead to a more accurate calculations of the utility parameters describing decisions of the players.

6.3 Simple Model of Horizon

In chapte 6.2 we demonstrated that in order to interpret decisions of proposers adequately, the model of the utility has to be used under the assumption that proposers do not always see all the available options. We have demonstrated that the effect of not noticing some options can be explained, at least to some extent, by the combinatorial complexity of the game. We have also demonstrated that this effect raises the question of measuring disagreement between the assumed utility and the given set of decisions. In this chapter we propose a mathematical model describing how the players notice the options. We will hereafter call this model the "model of noticing". In more detail, we present a probabilistic procedure that allows us to generate sets of noticed and unnoticed options given the set of available options. To make the model simple we keep the probability of an option to be noticed independent on the combinatorial complexity of this option as well as on its utility. We also demonstrate that any probabilistic model supplies us with a measure of disagreement and even for a simple model the corresponding measure performs better than the best measure presented in the previous chapter.

We start from one of the simplest possible models that assumes that every player can notice only a fixed limited number of options, which depends on the player. We will denote this number as r and the subset of all noticed options we will denote as r-subset. The above assumptions look quite natural since every player has a limited cognitive ability and every option, to be "noticed", has to be "calculated" by the player. Let us calculate the probability that a given option will be proposed within this model.

For all the available options, including the given one, we calculate a utility function. The set of the options can be split into two subsets. The first subset contains all the options that have a higher utility than the utility of the given option. We will call this subset as h-subset, where "h" denotes "higher". The second subset contains the remaining options - those options that have a utility lower than the utility of the given option. We will call this subset l-set, where "l" denotes "lower". Let us denote the size of the h- and l-subsets as h and l respectively.

The first condition for the option to be proposed is that it is noticed (*i.e.*, it is in the r-subset). The probability of this event is equal to $r/(h + l + 1)$ if $r < h+l+1$. In other words, the probability of the option to be in the r-subset is equal to the size of this subset (r) divided by the size of the whole set. The whole set consists of the given option, the options with utilities that are higher than the utility of the given options (h-subset) and the options with utilities that are lower than utilities of the proposed option (l-subset). The size of the whole set is equal to $h+l+1$. We also have to remember that for a given player the size of the set of noticed options (r-set) is fixed while the size of the set of all available options can vary from game to game. It can therefore happen that the size of the r-set is larger than the total number of the available options. In this case it can be said that the subject is able to notice all the options in the game and, as a result, the probability of the given option to be noticed is equal to one. Thus the probability that the given option will be noticed is equal to:

$$P = \max\left(1, \frac{r}{h + l + 1}\right). \tag{6.5}$$

For the given options to be proposed it is necessary to be noticed but it is not sufficient. The second necessary condition is that the given option has the highest utility in the set of all noticed options. In other words, none of the options from the h-set should be noticed. Let us calculate the probability of this event. The subset of the alternative options consists of the h- and l-subsets. There is C_{h+l}^{r-1} ways to choose (notice, in our terminology) $r-1$ options out of $h+l$ options, where C_k^n is used to indicate the binomial coefficients. We use $r-1$ instead of r because the given option is assumed to be noticed, as the result, there are $r-1$ options distributed over the h- and l-subsets. Now we need to calculate the total number of cases for which all $r-1$ options are in the l-subset and none of them are in the h-subset. The total number of these cases is equal to $C_h^0 \cdot C_l^{r-1} = C_l^{r-1}$. The above expression is equal to the number of ways to choose zero options from the h-subset (1 way) and number of ways to choose $r-1$ options from the l-subset. Accordingly, the probability that the given option will be proposed is equal to:

$$P = \max\left(1, \frac{r}{h+l+1}\right) \cdot \frac{C_l^{r-1}}{C_{h+l}^{r-1}}. \tag{6.6}$$

In the above formula we have to define the binomial coefficients such that they are equal to zero if $k > n$ in C_k^n. In this way the probability P will be equal to zero if $r-1 > l$. In other words, if the r-subset is larger than the $l+1$, then the subject will notice at least one option from the h-subset and, therefore, the given option will not be proposed. However, this definition of the binomial coefficients causes problems if $r > l+h+1$. In this case the binomial coefficients from the nominator and denominator are equal to zero and we have $0/0$ uncertainty. This situation happens if all options are noticed by the player. To calculate the probability that the given option will be proposed in this situation, we need to check the size of the h-subset. If it is equal to zero, then there are no options that have a higher utility than the given options and, as a result, the given option will be proposed with the probability 1. However, if the h-set is not empty, then there are options that dominate the given option and they all are noticed. Accordingly, in the described situation the probability for the given option to be proposed is equal to 0.

The measure of disagreement corresponding to the model described above has been tested on the set of real decisions. We have assumed the every player is able to notice only one option in addition to the default option. In this case the noticed option will be proposed only if its utility is higher than the utility of the proposed option. Within this model we can calculate the probability of a given sequence of decisions. This probability depends on the values of the utility parameters. Therefore, we can use this dependency to find the utility parameters that maximize the probability of the observed sequence of the decisions. The utility parameters found in this way were used to generate artificial decisions which, in turn, were used to calculate the populations of decisions of the three different types. The populations calculated in this way were compared with the populations of the real decisions, in the same way we demonstrated in chapter 6.2 about different measures of disagreement. The results of the comparison are shown in the last column of table 6.2. As we can see, the above described approach to the calculation of the utility parameters gives much better agreement with the real populations as compared to the approach based on use of disagreement measures. With the model-based approach we could remove the obvious underestimation of the cooperative populations observed in the case of the use of different measures of disagreement.

In the above example we have used $r = 1$ which assumes that players are able to notice only one option in addition to the default one. This assumption looks very unrealistic. It is more reasonable to assume a player is able to notice several options and then he/she chooses the option that maximizes his/her utility function. Following this logic we have increased r from 1 to 2. The populations of the three types of decisions, calculated with the new value of r, and the total deviation from the real populations are given in table 6.2. As we can see, in the case of $r = 2$ the systematic deviation is larger than in the case of $r = 1$. However, it is still smaller than the systematic deviation corresponding to the best constructed measure of inconsistency (utility distance).

The following question arises: How is it possible that a more realistic value of r ($r = 2$) provides a worse result than a less realistic value ($r = 1$)? Trying to understand this effect we start our reasoning from the fact that for large enough r, corresponding to the situation where a player is able to notice all the options, the probability of a given set of decisions will always be equal to zero independently of the values of the utility parameters. In other words, if we assume that a player is able to notice all the options then it should be possible to explain all his/her decisions by a single utility function. As we have discussed in the previous chapters, however, it is not the case. There is no single utility that could explain all decisions made by a given player (and this is the reason why we introduced the measures of inconsistency and the probabilistic models of noticing options). With the above described probabilistic model of noticing we were able to explain why the observed decisions are possible under an assumption of a fixed utility. However, this explanation did not work for some of the players. For example, for $r = 1$ there was one player for which the probability of the observed sequence of the decisions was equal to zero for all the utilities that we have tried. Moreover, for $r = 2$ we had already two such players. And if r is large enough, all players will have this property (probability of the observed sequence of the decisions will always be equal to zero independently of the assumed values of the utility parameters). In other words, by increasing r we decrease the number of players whose decisions can be explained by the model. So, we need to use small values of r to have a high predictive power of the model. The possible reason for that is the fact that there are many different reasons why players do not always choose the options that maximize a fixed utility and our model uses just one of the reasons (some options can be unnoticed by players). We therefore need to overexploit the mechanism included in the model (effect of unnoticing) to compensate for the absence of other mechanisms. One of the possible mechanisms that is not included in the introduced model could be the fact that users do not have a stable utility (*i.e.*, utility of players is different from game to game). Another possible mechanism could be the fact that players could miscalculate the payoffs corresponding to options. As a result, the user can propose an option not because it is noticed and it has the largest utility among the noticed options but because a player miscalculated the payoffs associated with the option.

On the basis of this reasoning we can conclude that the introduced probabilistic model of noticing is not realistic. This conclusion is rather expectable because the introduced model is far too simple to be realistic. Despite the fact that this model is not very accurate we have presented it for demonstrative purposes. First, we wanted to demonstrate that a measure of inconsistency can be naturally obtained from a model of noticing (as a probability of the given sequence of decisions). Second, we wanted to show that even with a very simple model we can get a better agreement with the experiment than we get with the constructed measures of inconsistencies. Finally, we wanted to demonstrate how a model of noticing can be constructed and used. In Appendix 11.2 we present another simple model of noticing and derive a more general model that combines the two simple models (one from this chapter and another from the appendix). The generalized model of noticing, presented in the appendix, depends on three parameters describing the way players notice options.

In the above examples we have fixed the parameter of the model (r) and use thed model with the fixed parameters to find the utility parameters of players. The utility parameters were found by minimization of the probability of the sequence of given decisions. We would like to note that the parameters of the model of noticing do not necessarily have to be fixed. We can run the minimization procedure over the utility parameters (as we have done up to now) and, at the same time, over the parameters of a probabilistic model of noticing. In this way, instead of predefining the values of the parameters of the model, we find the values that maximize the probability of the observed sequence of the decisions. In other words, we can use the given sequence of the decisions to find the parameters that describe cognitive capacity of a given player. These parameters can be included in the analysis in addition to the utility parameters. In particular they can indicate how mentally tired a person is. In the context of success of a mission, this knowledge can be as important as knowledge about the social utilities of the crew members.

The introduced probabilistic model of noticing is very simple and depends only on one parameter. A generalized model, which depends on three parameters, is given in Appendix 11.2. The generalization is made by assuming a more complex dependency of the probability for an option to be noticed on the number of options that are already noticed by a player. There are also other possible directions for generalization and improvement of the model. One of them is to tie the probability of noticing with the combinatorial complexity of the options. In chapter 6.1 we introduced three complexity parameters that could be used in a model of noticing. Another possible direction for the improvement of the model is to utilize the fact that different options can be grouped according to the trajectories with which they are associated. A player analyzes the state of the game in terms of the moves on the board that he/she and his/her opponent can make. Some combinations of the trajectories can be unnoticed and, therefore, the groups of the options associated with these trajectories can also be considered as unnoticed. The effect of the grouping of the options can be tied to the distribution of the number of unnoticed options over the games. For example, we can have many games in which the number of unnoticed options is equal to zero and few games in which the number of unnoticed options is very large. If we assume a high probability of noticing it is hard to explain the games in which there are a larger number of unnoticed options. On the other hand, if we assume a low probability of noticing, than it is hard to explain the games in which there are a small number of unnoticed options. The effect of grouping of options could provide an adequate explanation for the above described situations.

6.4 Utility Parameters of Participants

In the previous chapters we presented the utility function that describes cooperation and two different types of fairness (see equation 5.47). We have also introduced different measures of disagreement between a given set of decisions and a given set of utility parameters. By minimization of these measures we can find a set of utility parameters that corresponds to a given set of decisions. However, we have also demonstrated that within this approach we could get a systematic under- or over-estimation of fair or cooperative components of the utility function. To solve this problem we have proposed an alternative approach. Within the new approach we need to construct a probabilistic model of noticing options instead of a measure of disagreement. We have demonstrated that with the model-based approach we can significantly reduce the systematic deviation between the real populations of the decisions of different types and simulated populations obtained with a derived utility function. In this chapter we apply the model-based approach to calculate the utility parameters of different participants based on their proposals made in the CT game. In more detail, we use the simple probabilistic model that the parameters which provide the smallest systematic deviation between the real and simulated populations of the decisions of different types.

We have calculated the utility parameters of 21 players (seven teams including two teams from the Mars-500 experiment). In figures 6.6-6.8 we show the calculated utility parameters. Since every utility function is given by three utility parameters (ω, f and g), the utility function of each player can be presented as a point in the 3D space of the utility parameters. To present the utility parameters of the considered players we use three different 2D projections of the 3D utility space. In more detail, we project the points into the (ω, f), (ω, g) and (f, g) subspaces.

In figures 6.6-6.8 we can see the following properties of the utility parameters. First, the values of the utility parameter ω, which is responsible for cooperation, are distributed around the value corresponding to the optimal cooperation (0.25). The smaller values of ω indicate that a subject cares more about his/her own benefit than the benefit of his/her opponent. The values that are larger

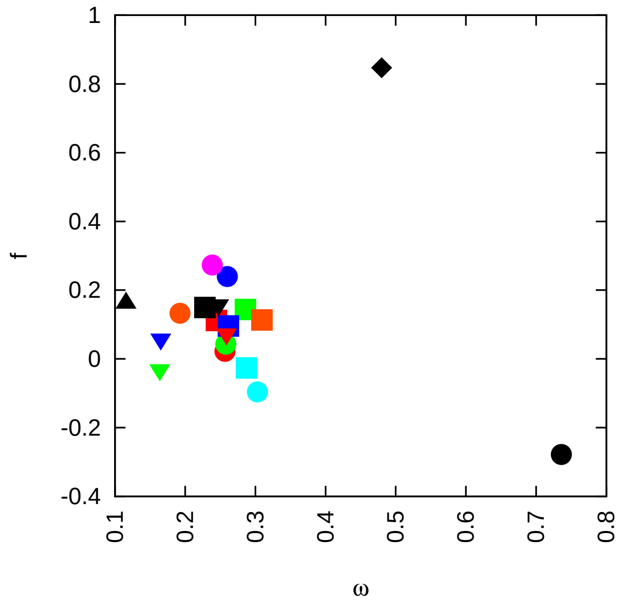

Fig. 6.6: Utility parameters of players shown in terms of the cooperativeness ω and fairness with respect to the final score f

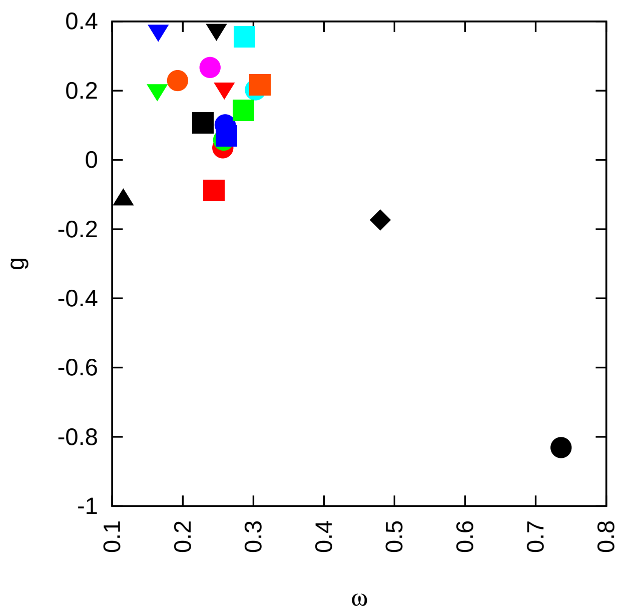

Fig. 6.7: Utility parameters of players shown in terms of the cooperativeness ω and fairness with respect to the gain g

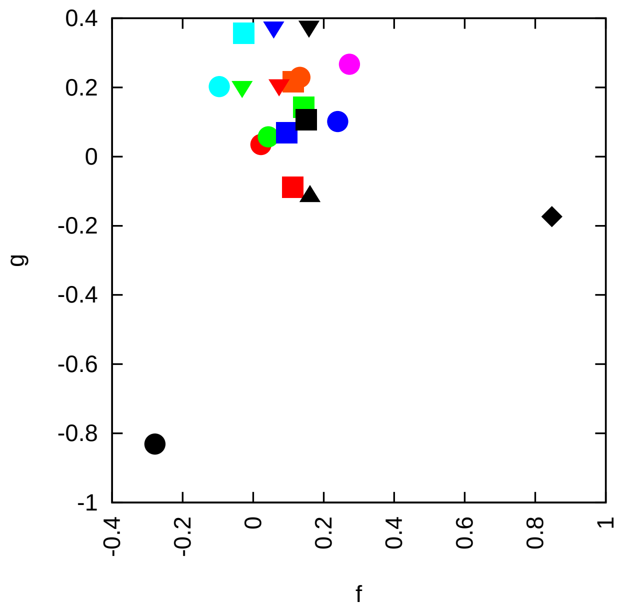

Fig. 6.8: Utility parameters of players shown in terms of the fairness of two different types

than 0.25 mean that the subject cares more about the benefit of the opponent than about his/her own benefit. The parameter ω equal to zero means an absolutely egoistic player, who does not care about the payoff of his/her opponent at all. Another extreme case corresponds to $\omega = 0.5$, which corresponds to an absolutely altruistic player who cares only about the payoff of his/her opponent and does not care about his/her own payoff. In this context it is interesting to note that in all cases ω was larger than 0.1 and in most of the cases it was smaller than 0.35. This means that most of the players balance between their own payoffs and payoffs of their opponents. The two exceptions, corresponding to extremely large values of omega are most likely to be explained by an inaccuracy of the values of the parameters. Another observation is that in most of the cases the value of the parameters corresponding to the two different kinds of fairness (f and g) are larger than zero. This means that most of the players care about fairness of the proposals. It is also interesting to note that players tend to care about fairness of the gain slightly more than about fairness of the final score. For such players it is less important how much everyone will have after an exchange. For them it is more important how much everyone gets in addition to what everyone already had before the exchange. Finally we should note that the range of the distribution for all three parameters is approximately the same (about 0.5).

As we can see in figures 6.6-6.8 the values of the utility parameters form a quite homogeneous cluster. In particular we cannot see a clear relation between the utility parameters. For example we cannot say that cooperative players tend to care less about fairness. This distribution of the values and a rather small number of games per player raises the question whether the observed difference between the utility parameters of the players is statistically significant or if it is just noise.

To answer this question we have made a pair-wise comparison of all players. For every pair of players we have calculated the difference between the utility parameters that describe their play behavior. The difference has been calculated as a Euclidian distance between the two points representing the utility parameters of two players in the 3D utility space. After that, for a given pair of players we have put their decisions in one set, shuffled these decisions and split the combined set into two subsets of the same sizes as the original two subsets. For the two new subsets of decisions we have calculated the utility parameters as well as the difference between them. For a given pair of players we have repeated this procedure many times to find out in what percentage of cases the difference between the two "fake" utility parameters is smaller than the original distance between the real utility parameters of the two considered players. This percentage has been calculated for all possible pairs of players. The distribution of the values of these percentages is shown in figure 6.9.

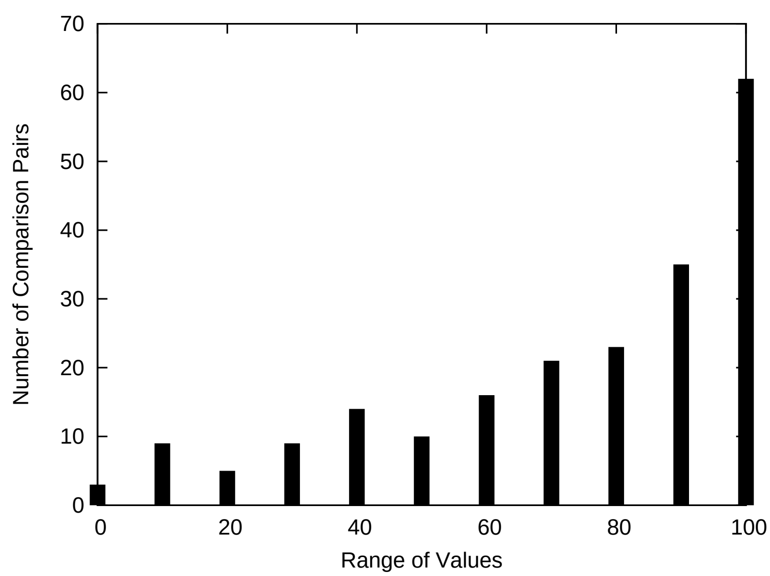

Fig. 6.9: Distribution of the percentage of cases in which the distance between the fake utility parameters has been smaller than the distance between the real utility parameters of two given players

As we can see from the distribution shown in figure 6.9, the larger values of the percentage are populated more than the smaller values. This means that there is a tendency for the pairs of the real utility parameters to be more distant from each other than the pairs of the fake utility parameters. In the case where there is no difference between the players in terms of the utility parameters the distribution shown in figure 6.9 has to be homogeneous. To make a solid conclusion we have calculated the p-value of the null hypothesis assuming that the players are not distinguishable in terms of the utility parameters and the given deviation of the distribution from the homogeneous one is obtained just by chance. The calculated p-value was found to be extremely small (less that 10^-10). From that fact we can conclude that players differ from each other in terms of the utility parameters that characterize their play behavior.

Finally we would like to emphasize that the difference between the players, for which the statistical significance has been calculated, is cumulative. In other words, we have calculated the p-value of the null hypothesis assuming that all the players are the same. If instead we try to compare a pair of players, we will find that in many cases the difference between them is statistically insignificant. We can see this from the distribution 6.9. For a larger portion of the pairs of players the distance between their utility parameters can be as large as it is (or even larger) just by chance.

The main conclusion of this chapter is that the values of the utility parameters of any two players are not accurate enough to be compared with each other and analyzed in detail. However, the accuracy is good enough to draw conclusions about collective properties (distribution) of the values for the considered group of players. In particular we can get a good idea about what the expected values of the utility parameters are and how broadly they are distributed and what the shape of the distribution is. Moreover, we have a convincing reason to believe that players differ from each other in terms of their utility parameter and, accordingly, these parameters can be used to characterize players in a meaningful way. For a further and better application of this method we would recommend using games in which players can make their decisions more frequently and with a smaller cognitive effort. In this way a much larger set of decisions can be generated and, therefore, utility parameters can be calculated with much higher accuracy.

7. ANALYSIS OF THE BEHAVIOR OF THE RESPONDERS

In this chapter we switch from the analysis of the proposal phase of the CT game to analysis of the response phase. In the response phase of the game players needed to choose one proposal from the set of available proposals. This phase of the game is different from the proposition phase in two ways. First, in the response phase the player has a much smaller number of options from which to choose (from one to three options). We therefore get much less information about the preferences of the player over different combinations of payoffs. Second, every option in the proposition phase involves payoffs of two players while options in the response phase always involve payoffs of three players. These two differences are quite significant and require a development of alternative approaches for the analysis of the response data. Specifically, a direct generalization of the utility function from the case of two players to the case of three players increases the number of the utility parameters from three to eight. The more parameters we have the more data we need to find the values of these parameters with reasonable accuracy. However, in the response phase we have less data because in this phase the chosen option can be compared with only one or two other options while in the proposition phase the chosen option can always be compared with tens of other (not chosen) options, and every comparison provides some information needed for the parameterization of the utility function. Moreover, the approach based on the cooperation ratios and developed for the proposition phase cannot be directly used for the analysis of the response phase. To use this approach in the proposition phase we needed to calculate populations of three different types of decisions (asking for help, proposing help and mutually beneficial propositions). In contrast to the proposition phase, the options in the response phase qualitatively differ from each other not only by how beneficial they are to the players but also by who proposed them and to whom. As a result, instead of three types of decisions we have 12 types of decisions. Moreover, a calculation of the populations of different kinds of decisions cannot be used directly to describe preferences of a given responder over these types of options. The reason for that is that populations of different kinds of decisions, made by the responder, are conditioned not only by the preferences of the responder but also by what proposals a given responder receives. For example, it can happen that a given responder never accepted mutually beneficial proposals from the second opponent just because he/she never received proposals of this type.

To address the features of the response phase properly we first introduce a simple linear utility and discuss how to parameterize and visualize it. After that,

	user1	user2	user3	user4	user5	user6
Number of Decisions	60	18	21	25	51	20
Pareto Dominating	23.3%	16.6%	19.0%	8.0%	17.6%	35.0%
No Strict Domination	63.3%	33.3%	61.9%	72.0%	60.8%	60.0%
Pareto Dominated	3.3%	22.2%	9.5%	8.0%	7.8%	0.0%
Identical Options	10.0%	27.8%	9.5%	12.0%	13.7%	5.0%

Tab. 7.1: General statistics of the decisions made in the response phase during the Mars-500 experiment

to overcome the shortcomings of the simple linear model, we propose an alternative analysis based on the definitions of different types (or classes) of decisions. We visualize the preferences of the responder over these classes and propose a way to describe these preferences in a numerical way. Finally, we present a link between this approach and the approach based on the cooperation ratios used in the proposition phase. This link is used to compare results from the two phases of the game. This comparison shows a statistically very significant correlation between the preferences of the players in the different phases of the game. This correlation serves as a convincing indication that the numerical properties describing social preferences of the players in different phases are meaningful (not just noise).

7.1 Linear Model of Responders Preferences

In the response phase a responder needs to choose between his/her own proposal and proposals made to the responder by other players. Every responder can have one, two or no proposals from other players. If in a response phase a player had three options (A, B and C) and option C has been chosen, we can say that the player decided that (1) option C is better than option B and that (2) option C is also better than option A. So, we can say that the considered response phase reveals two decisions of the player. The total number of the decisions made by every player is given in table 7.1. The different number of decisions made by the players is caused by the fact that different players receive different numbers of proposals.

To be able to make a quantitative analysis of the decision- making process in the response phase we need a formal way to describe the options available to the responder. One of the simplest approaches is to describe every option by the points that will be received by every player in the event the option is implemented (*i.e.*, every option is described by three numbers). This simple description of the options makes it possible to compare the options in terms of the Pareto optimality. One of the possible relations between two given options is that one of the options is clearly better than the other one. For example, option $[90, 55, 110]$ is clearly better than option $[80, 55, 100]$ since in the case of the first option the first and third player get more points and the second player does not get less. In this case we can say the first option is Pareto-dominating the second one (or the second option is Pareto-dominated by the first one). Strictly speaking the first option dominates the second one if all three payoffs corresponding to the first option are larger than or equal to the three payoffs corresponding to the second option and not all payoffs of the first option are equal to the corresponding payoffs of the second option. It is also possible that none of the two options dominates (or is dominated by) another option. For example neither of the following two options $[150, 100, 50]$ and $[140, 120, 50]$ dominates the other one. The first option gives a larger payoff to the first player while the second option gives a larger payoff to the second player. Finally we can have a case where a responder needs to choose between two identical (in terms of the payoffs) options.

As we can see in table 7.1, from 8.0% to 35.0% of cases players chose options that strictly dominated the alternative option. In simple words we can say that in the considered cases the responder chose options which are better at least for someone (may be even for everyone) and are not worse for anyone. Since the chosen options are clearly better than the alternatives, the choices are trivial and, as a result, they are not very interesting for the analysis.

In most of the cases players had to choose between options that did not dominate each other (see "No Strict Domination" line in table 7.1). In the considered cases, responders needed to make decisions in situations where one of the options is better for one player and another option is better for another player. In these situations the responder needs to balance between payoffs of different players and, therefore, these decisions can reveal the value of the payoffs of other players to the responder. In particular, by analysis of the decisions of this kind, we can determine how much the responder is ready to sacrifice for the benefit of others and what sacrifices of others for the benefit of the responder are acceptable to the responder.

There are also cases in which a responder chose strictly dominated options. In these cases options that are not better for anyone and are worse for at least one player were chosen. For five out of six players the percentage of these choices was smaller than 10.0 and for the second user it is equal to 22%. There are two possible explanations for this kind of decision. First, it is possible that the responder just miscalculated the outcomes corresponding to different options. Second, it can be that responders have so called Pareto-damaging utility functions, which means that they can, for example, reduce the payoff of all the players to reduce a difference between the payoffs of different players and to make, in this way, the outcome "fairer".

Finally we have cases in which a responder needed to choose between two equivalent (in terms of payoffs) options. These choices are interesting since the points associated with the options cannot determine the choice and, as a result, some psychological preferences can be revealed. For example, by analysis of decisions of this kind we can determine if the responder prefers proposals of the first or the second partner or if he prefers to accept pro posals that he made rather than proposals made by other players.

For example there were five cases in which participant 1 had to choose between his own proposal and an identical (in terms of the payoffs) proposal of participant 2. In four out of five cases the responder decided to choose his own proposal. So, it can be that the considered participant prefers to stay with his own proposal rather than to accept somebody else's proposals. However, the number of the cases is not large enough to make a solid conclusion about the preferences of the responder. If we assume that preferences of the decisions over different options depend only on the payoffs associated with the options and do not depend on who proposed the option, then the probability of the mentioned observation is still quite high (0.156). On the other hand, the pattern observed for the first participant is supported by decisions of the second participant. In five cases out of five, the second participant decided to switch to (accept) the proposal of the first participant despite the fact that his own proposal was identical in terms of the payoffs. The third participant, who played in the same team as the first two, had to choose between the identical options only two times which is not enough to find a pattern. Participant 4 needed to choose three times between his own proposals and identical proposals made by participant 5. In all three cases participant 4 decided to stay with his own proposal. Participant 5, when he needed to choose between identical options, decided to stay with his own proposal in six cases out of seven. Finally, participant 6 needed to choose between identical proposals only once, so no pattern can be identified for this participant.

Alternatively, every option can be characterized by the gains of points by every player (with respect to the default option). In a more complex model we can use both sets of parameters: the final scores and the gains. In this case, every option is described by six numbers. From a geometric point of view, in the response phase a player (responder) needs to choose one of two or three points in a six dimensional space.

As the simplest approximation we can assume that responders always chose those options that give them the largest final score (the largest score automatically provides the largest gain). To describe such a behavior a more complex model is needed. We assume that responders care about payoffs of other player. The simplest way to combine scores of other player is to use the linear model:

$$a_{ij} = \sum_{k=1}^{3} f_{ik}\omega_{kj}, \tag{7.1}$$

where a_{ij} is the attractiveness of option i to the player j, f_{ik} is the final score received by the player k under the condition that option i is implemented and ω_{kj} is the importance of player k to player j. In other words, to calculate the attractiveness of an option to a player, we make a loop over all players, for every player we calculate the final score corresponding to the considered option and multiply the score by the importance of the considered player to the player who evaluates the attractiveness of the option.

It needs to be noted that within the linear model it does not matter if we use the final scores or the gain of scores. If $\omega_1(x_1^0 + \Delta x_1^1) + \omega_2(x_2^0 + \Delta x_2^1) > \omega_1(x_1^0 + \Delta x_1^2) + \omega_2(x_2^0 + \Delta x_2^2)$ than $\omega_1 \Delta x_1^1 + \omega_2 \Delta x_2^1 > \omega_1 \Delta x_1^2 + \omega_2 \Delta x_2^2$, where x_1^0 and x_2^0 represent the score obtained by of the first and the second players in the case of the default (no exchange) option. The term Δx_j^i represents the gain of score obtained by the j_{th} player if the i_{th} proposal is accepted.

We normalize the weighting factors ω_{kj}, describing the behavior of j_{th} responder, to count for insensitivity of the model to a positive scaling factor ($\omega_{kj} = \alpha\omega_{kj}$ and ω_{kj} give the same behavior of the responder if $\alpha > 0$). The following normalization condition is applied:

$$\sum_{k=1}^{3} \omega_{kj} = 1. \tag{7.2}$$

In this way we reduce the number of degrees of freedom describing behavior of responders from three to two. Taking into account the normalization condition we can represent behavior of a responder as a unit vector in a three-dimensional space (or as a point on a sphere). In this case it is convenient to use spherical coordinates to specify the behavior of a responder. The usage of the spherical coordinates also explicitly provides two parameters (spherical coordinates) corresponding to the two above mentioned degree of freedoms.

$$\begin{aligned} \omega_{1j} &= \sin(\theta_j)\cos(\beta_j), \\ \omega_{2j} &= \sin(\theta_j)\sin(\beta_j), \\ \omega_{3j} &= \cos(\theta_j). \end{aligned} \tag{7.3}$$

By convention the z-component indicates the importance of a player to himself/herself. In this way, the absolutely egoistic responder is described by $\theta = 0°$. If $\theta = 90°$, the responder does not care about his/her own score. The x- and y-directions correspond to other players. For example, if the considered player (z-player) does not care about the score of the y-player and does care about the score of the first player (x-player), then $\beta = 0°$.

The models of the responders have been parameterized in the following way. For every responder we have considered all situations in which the responder needed to choose between two or three options. Every option was considered as a 3D-vector of scores: f_{ik}, where i is used to indicate the vector (option) and k is used to indicate components of the vector (every component corresponds to a player). In this way, every situation, in which a responder needs to make a decision, is characterized by two or three 3D-vectors. The decision itself is characterized by the chosen vector.

For every situation we considered different models given by the values of θ and β angles. The two angles were given on a grid with the step equal to one degree. For every model (pair of values for θ and β angles) we have calculated the attractiveness of every option. By this construction the model predicts that the responder chooses the most attractive option. The prediction of the model was compared with the real decision of the responder and the number of contradictions with the real decision was calculated. The contradictions were calculated in the following way. If a responder had three options ("a", "b" and "c") and he/she chose option "a" then we can conclude that for the considered responder "a" is better than "b" and "a" is better than "c". Let us assume that

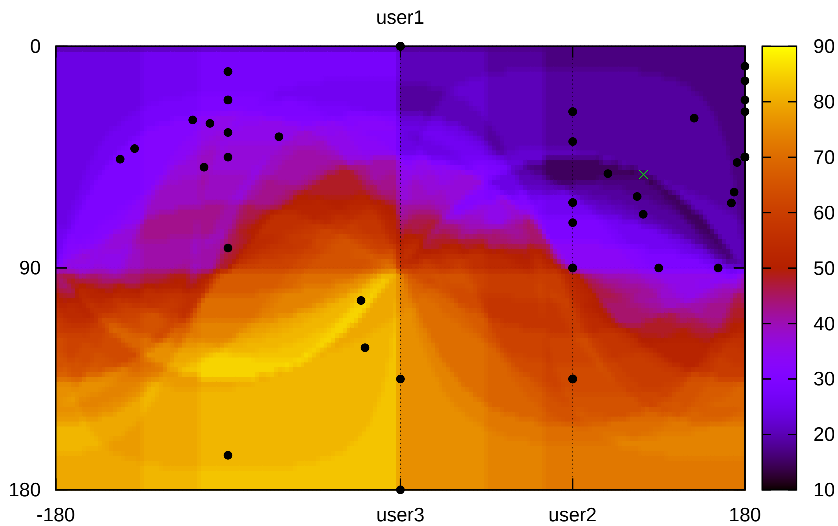

Fig. 7.1: Visualization of the linear model of responses for the $user_1$ from the Mars-500 experiment

according to a considered model "b" is better than "a" and "a" is better than "c". In this case the considered model (given by values of β and θ) generates one contradiction with the real situation. For every pair of values of β and θ angles we have calculated the total number of contradictions using all available decisions of the responder. In this way every point on the sphere (space of models) is mapped into the number of the contradictions of the model with the real behavior of the responder. An example of such a model is shown in figure 7.1 - 7.2.

Having the mapping of β and θ angles into the number of contradictions with the data, we chose those regions that provide the minimal number of contradictions. For all points in the regions providing the minimal number of contradictions we chose one point that is the most distant from the border of the region. In this way we get two numbers describing behavior of responders.

The size of the region giving the minimal number of contradictions indicates the accuracy of the β and θ angles. In other words, we could have a set of models that provide the same level of agreement with the real behavior. The size of this set goes to zero when the size of the input data grows.

The minimal number of contradictions represents the predictive power of the model (*i.e.*, how frequently prediction of the model agrees with the real decisions of the responder). We can expect a certain number of contradictions with the real data because of two main reasons. First, a player can miscalculate payoffs associated with different exchanges. Second, the linear model is too simple to capture all factors influencing decisions of the responders. In particular the linear model does not compare made proposals with those ones that could be made. This comparison plays a crucial role in rewarding and punishing behavior

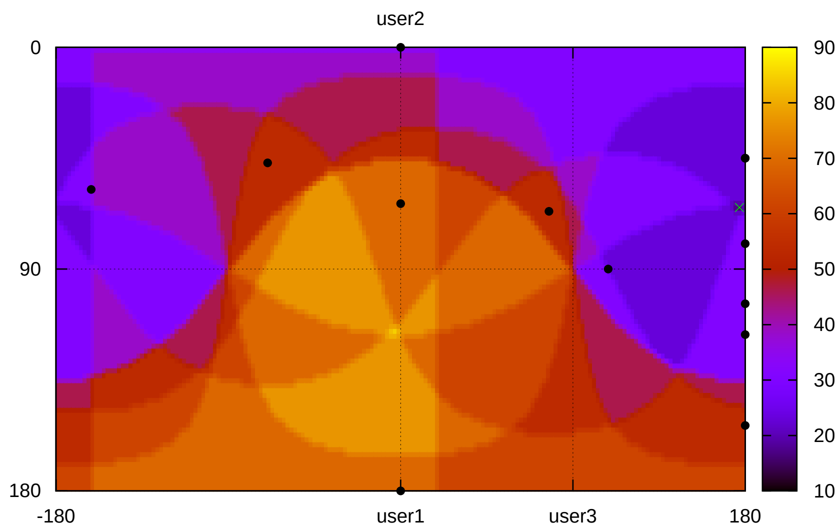

Fig. 7.2: Visualization of the linear model of responses for the $user_2$ from the Mars-500 experiment

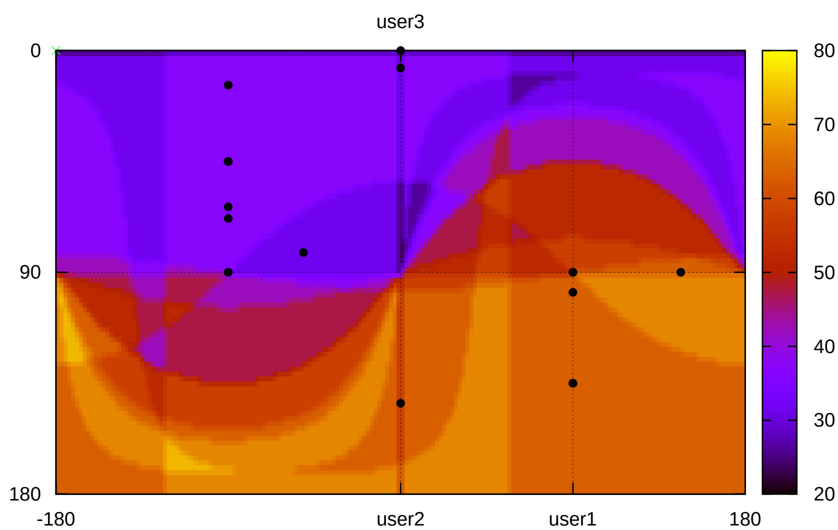

Fig. 7.3: Visualization of the linear model of responses for the $user_3$ from the Mars-500 experiment

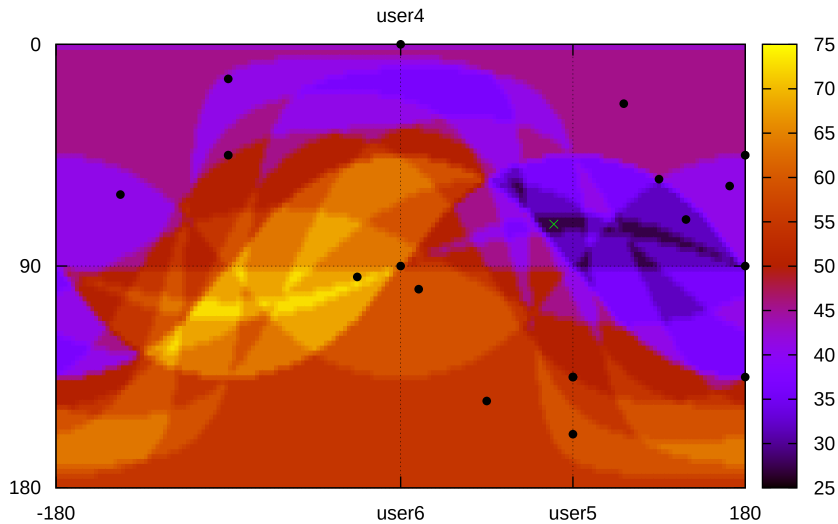

Fig. 7.4: Visualization of the linear model of responses for the $user_4$ from the Mars-500 experiment

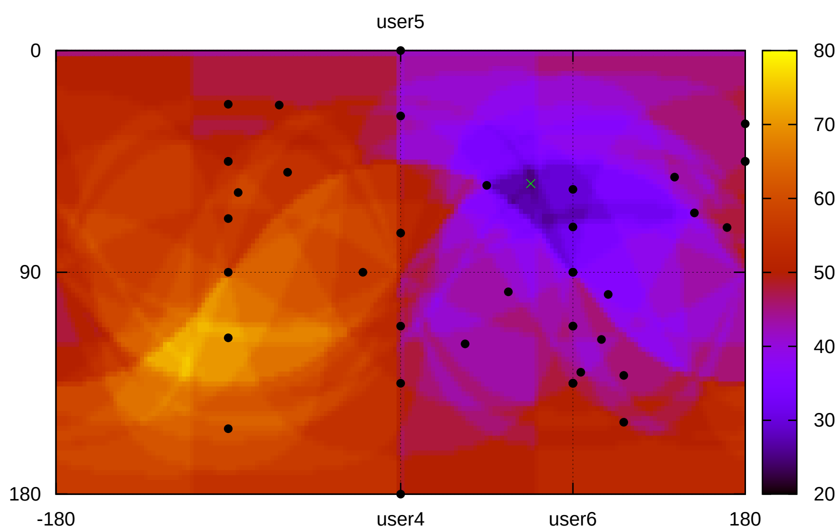

Fig. 7.5: Visualization of the linear model of responses for the $user_5$ from the Mars-500 experiment

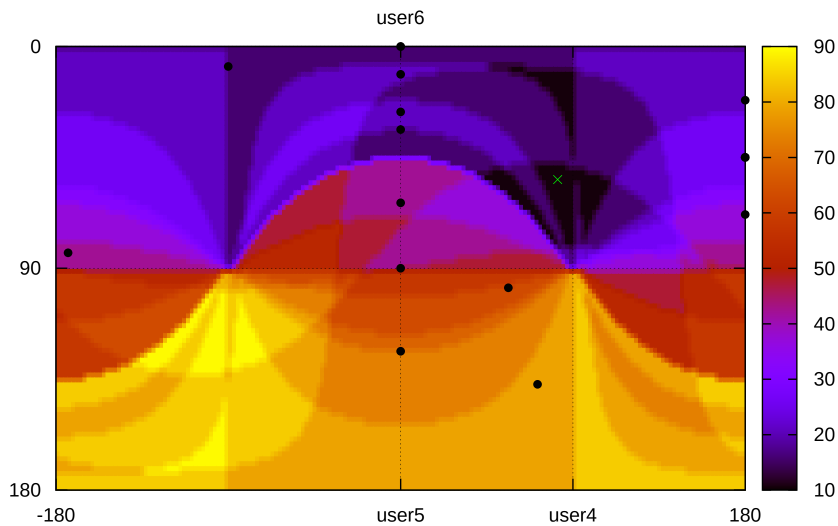

Fig. 7.6: Visualization of the linear model of responses for the $user_6$ from the Mars-500 experiment

when a responder rewards the desired proposals and punishes the undesired ones. Moreover, the linear model is assumed to be static (β and θ are time independent) and, therefore, it cannot capture retrospective and prospective thinking which makes the behavior of the responder dependent on previous and future games.

To improve the model for the responders we need to take into account not only payoffs provided by an option but also the probability that an option will be implemented under the condition that it is accepted by the responder. In more detail, an option (exchange) is implemented only if both participants of the exchange agree to implement it. In other words, it is possible that an option is not implemented despite the fact that it is accepted by the responder. However, for some "secure" options the decision of the responder is the only factor that determines whether the option will be implemented. The "secure" options come from proposers who have no other options except their own. In these situations the proposer cannot change his/her mind and need to stay with his/her own option.

To calculate the probability that an option chosen by a responder will be implemented we assume that other responders chose options randomly. Under this assumption the probability that an "unsecure" option will be implemented (under the condition that it is chosen by one responder) is equal to 0.5. To calculate the attractiveness of such an option we dilute payoffs of this option with the payoffs of no-exchange options. After the corrected payoffs of an option are calculated we apply the same procedure as before to parameterize the models of responders.

7.2 Network of Preferences

In the previous section we constructed a linear model based on the assumption that responder values the available options using payoffs of all the players. However, it is possible that a relation between the proposers' and responders' benefits is more important for a responder. It is natural for humans to describe options in terms of help (*e.g.*, who asks for help, who proposes help, how large is the proposed/requested help, what is the price/sacrifice of the help). To capture this kind of thinking we split all possible exchanges into three qualitatively different classes: mutually beneficial exchanges, exchanges in which proposer offers help to responder, exchanges in which proposer asks responder for help. These three classes of exchanges can be proposed by the player or to the player. Moreover, every player has two partners. This means that every responder can have 12 different types of options. In this domain, behavior of a responder can be described by the attractiveness of the different kinds of proposals. In other words, the model of a responder is given by an ordered sequence of 12 types of options. Or, in a more accurate model, each type of option corresponds with a real number describing the attractiveness of the exchanges of a given type.

In the response phase a player chooses one of two or three options. Every option can be represented by its type. So, a decision of a responder can be visualized as an arrow pointing from types representing the rejected options to the type of the accepted option. By collecting decisions of responder in all available games we can build a directed graph with 12 nodes representing twelve different types of exchanges. This visualization is shown on figures 7.7 - 7.12. Two nodes can be connected several times by the same connection because the first option can be preferred by a considered player over the second one in several games. In this case we put the number indicating how many times the given connection has been observed in the data. The options of different kinds are marked as "gh", "mb", and "ah" meaning "give help", "mutually beneficial", and "ask help", respectively.

To analyze the networks of decisions of responders we have applied the Page rank algorithm to rank every node (class of exchanges). In this way we could get a number representing the attractiveness of every node to the corresponding responder.

Interesting regularities have been observed and will be summarized below. In the first team the first player tends to prefer interaction with the first partner. In seven cases the player had a choice to interact with the first or second partner. In five cases an exchange with the first partner has been chosen. Both chosen exchanges with the second partner involve help proposed by the second partner.

While the first player tends to have a preferable partner, the third player seems to pay attention on the type of exchanges. By using the Page rank for different exchanges we found that the first three places are occupied by mutually beneficial exchanges. The next three places are occupied by exchanges in which proposer asks for help. Following are four exchanges in which the proposer offers help. The only exception is a mutually beneficial exchange occupying in the last place.

In the second team the first player exhibits an exploiting behavior toward his/her second partner. In more detail, the help proposed by the second partner strongly dominates over all other types of exchanges. In spite on the helping behavior of the second partner, the first player never chose an exchange in which he/she provides help to this partner.

The second responder in the considered team exhibits a helpful behavior towards the second partner. In particular, the considered player proposes helpful or mutually beneficial exchanges to the second partner and then, on the response phase, he/she stays with his/her own proposals.

The third user in the second team, similarly to the third player in the first team tends to evaluate proposals based on their type. However, the order of the preferences is different. The first three places are taken by exchanges in which proposer offers help. The next two places are occupied by mutually beneficial exchanges and the last three places are taken by proposals in which proposer asks for help.

In the third team the first player tends to dominate over the second partner. In six cases out of seven proposals from the second partner were not accepted. The only accepted proposal from the second partner was an exchange in which the second partner proposed help. In four out of the seven cases the considered player decided to accept his/her own proposal to the second partner. The considered player also tends to expect help from the first partner. This player accepts his/her proposals only if they request help. In contrast the considered responder never chose the proposal in which help is requested from the second partner.

The second player in the third team tends to have preferences towards the second partner. The first four types of the proposals involve exchanges with the second partner. After these exchanges we have those which involve the first partner (with only one exception). Moreover, the considered player expects a collaborative interaction with the second player. In particular the player chooses exchanges in which he/she requests help from the second player. The player is also ready to provide help to this partner.

The third player in the considered team tends to have preferences to the type of exchanges. In particular all exchanges in which proposer asks for help have the smallest rank. All mutually beneficial exchanges made by this player have the highest ranks. The only exception is an exchange in which the first partner proposes help to the considered player. Exchanges of these type occupy the first place in the ranked list of options.

The rank of every class of exchanges is nothing but the population corresponding node in the jumping process performed by the Page rank algorithm. Having these populations we can define parameters describing behavior of the responders in the way similar to those used in the proposal phase. The 12 populations corresponding to the 12 nodes of the diagram are tied by the normalization conditions (sum of all the numbers is equal to one hundred). As a result we have 11 independent degrees of freedom which can be combined to get 11 independent parameters describing the behavior of every responder. These parameters should be defined in a way providing a clear interpretation and a

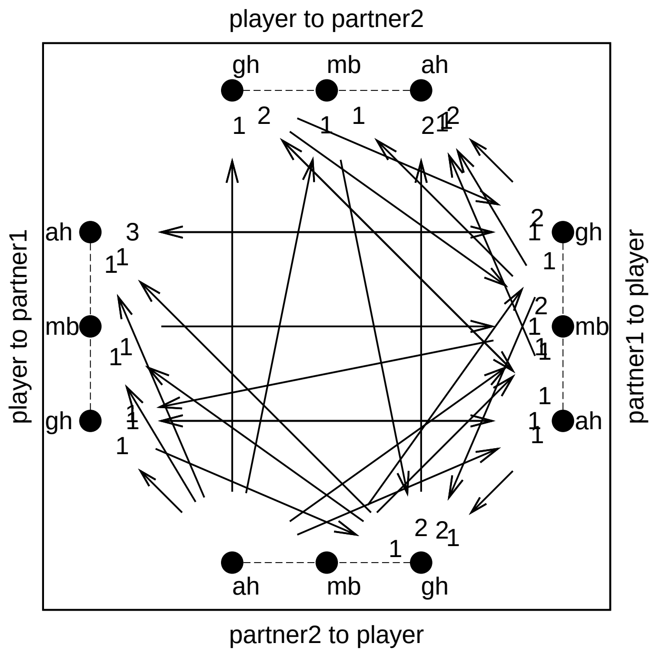

Fig. 7.7: Network of preferences of user1

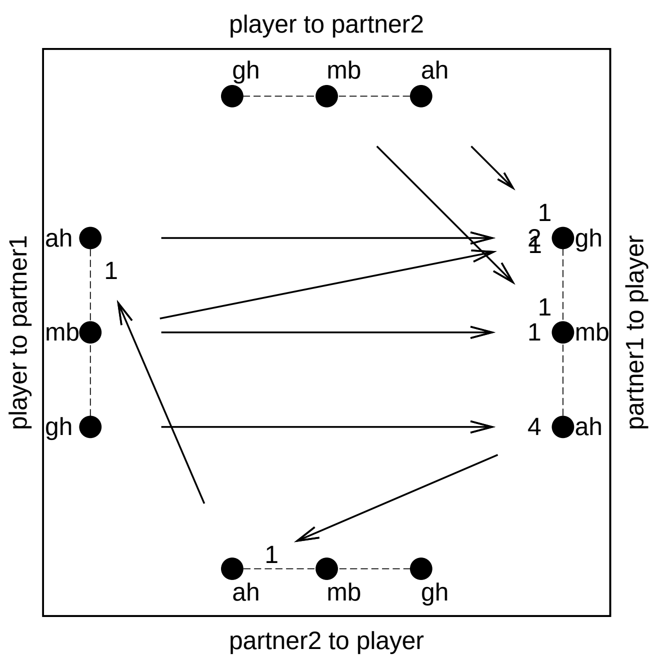

Fig. 7.8: Network of preferences of user2

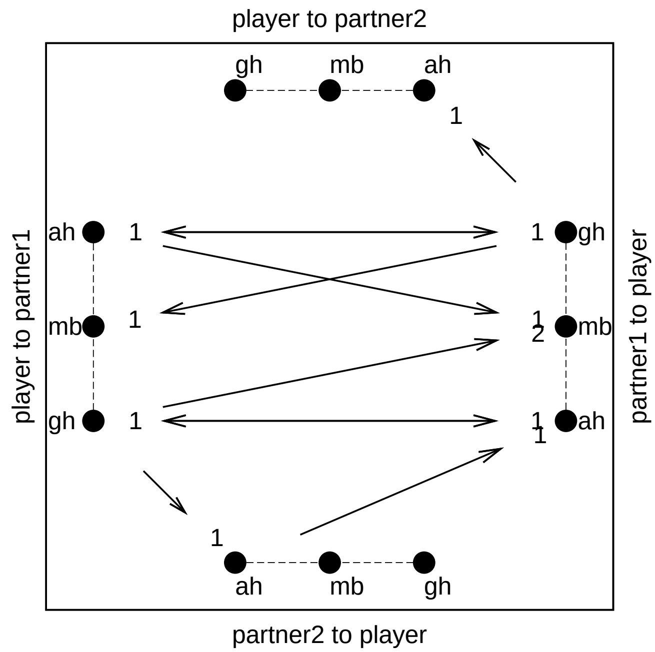

Fig. 7.9: Network of preferences of user3

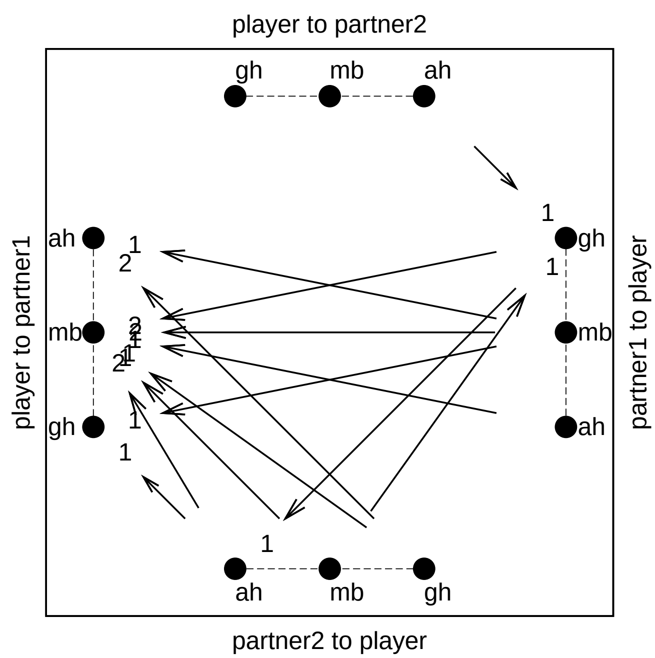

Fig. 7.10: Network of preferences of user4

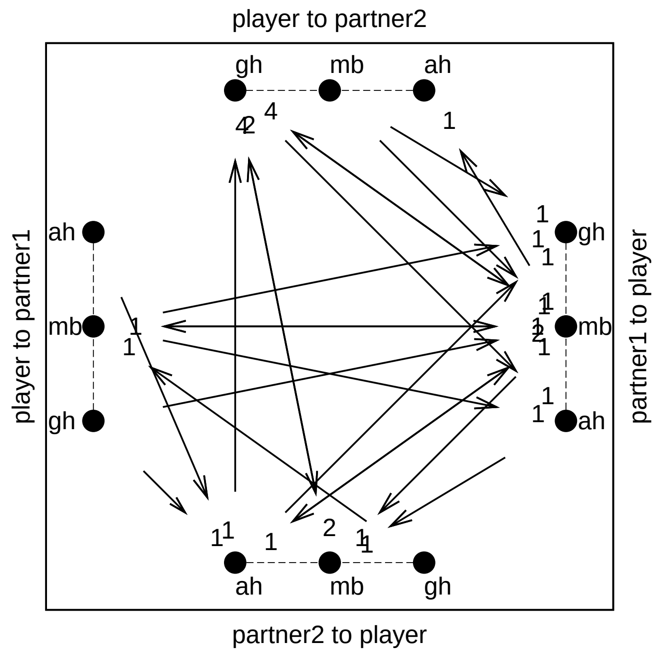

Fig. 7.11: Network of preferences of user5

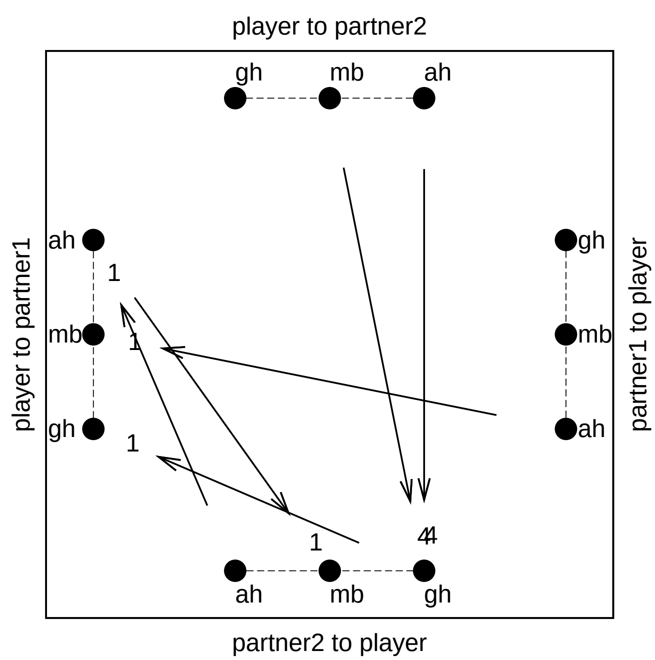

Fig. 7.12: Network of preferences of user6

clear relation with parameters describing the behavior of proposers.

First we consider partners of a given player independently. As in the proposal phase responder has three kinds of exchanges with a given partner: exchanges providing help from the responder to the partner, mutually beneficial exchanges and exchanges providing help to the responder from the partner. As in the proposal phase we can use two numbers to describe relative populations of all three kinds of exchanges (help ratio and give ratio).

$$\nu_{i,hr}^{(j)} = \frac{r_{ah}^{(ij)} + r_{ph}^{(ij)}}{r_{mb}^{(ij)} + r_{ah}^{(ij)} + r_{ph}^{(ij)}}, \tag{7.4}$$

$$\nu_{i,gr}^{(j)} = \frac{r_{ph}^{(ij)}}{r_{ah}^{(ij)} + r_{ph}^{(ij)}}, \tag{7.5}$$

where i and j indices are used to indicate the proposer and responder, respectively.

In contrast to the proposal phase, the exchanges are distinguished not only by who provides and who gets help (as a result of the exchange) but also who has proposed the exchanges (considered player or his/her partner). For example, help from the partner to the considered player can be either asked by the player or proposed by the partner. We can assume that these two kinds of exchanges can be treated differently by the player. In summary we can say that in a general case we need to use two parameters to describe preferences of a responder over different kinds of his/her own proposals. To describe preferences over different kinds of proposals offered by the partner we need to use another pair of parameters (with the identical meaning).

$$\mu_{i,hr}^{(j)} = \frac{r_{ah}^{(ji)} + r_{ph}^{(ji)}}{r_{mb}^{(ji)} + r_{ah}^{(ji)} + r_{ph}^{(ji)}}, \tag{7.6}$$

$$\mu_{i,gr}^{(j)} = \frac{r_{ah}^{(ji)}}{r_{ah}^{(ji)} + r_{ph}^{(ji)}}. \tag{7.7}$$

We also need to use one more parameter that indicates if a responder prefers to accept his/her own exchanges rather than exchanges from his/her partner.

$$d_i = \frac{r_{mb}^{(ij)} + r_{ah}^{(ij)} + r_{ph}^{(ij)}}{r_{mb}^{(ji)} + r_{ah}^{(ji)} + r_{ph}^{(ji)}}. \tag{7.8}$$

In this way we get five parameters describing behavior of the responder with one of his/her partners. For another partner we use another five parameters. So in total we have ten parameters. One more parameter should be used to describe inter-partner behavior of the responder. Or, more specifically, the last parameter should indicate how strongly the considered responder prefers to interact with one of the partners.

$$p_i = \frac{r_{mb}^{(ij)} + r_{ah}^{(ij)} + r_{ph}^{(ij)} + r_{mb}^{(ji)} + r_{ah}^{(ji)} + r_{ph}^{(ji)}}{r_{mb}^{(ik)} + r_{ah}^{(ik)} + r_{ph}^{(ik)} + r_{mb}^{(ki)} + r_{ah}^{(ki)} + r_{ph}^{(ki)}}. \tag{7.9}$$

7.3 Correlation between Proposal and Response Phases

In the previous sections we used populations of the different kinds of proposals made by a given proposer to calculate the two cooperation ratios namely the level and the symmetry of cooperation. All proposals have been split into three classes: (1) proposals beneficial for both players (the proposer and the responder), (2) proposals in which a player proposes to sacrifice his/her own benefit for the benefit of the other player, and (3) proposals in which the proposer asks the partner to sacrifice his/her benefit for the benefit of the proposer.

To analyze the decisions of a player in the role of the responder we have used the 12 different classes of the proposals. As in the case of the proposals phase, the proposals are classified according to who benefits from them (the proposer, the responder or both), and who is the partner in the exchange (the first or the second player). Additionally, the exchange can be characterized by who made it. For example, in the response phase a player can have two identical exchanges with the same partner but the first exchange is proposed by the considered player to his/her partner while the second one is proposed by his/her partner to the considered player.

The similarity between the classification of the options available to the players in the proposal and response phases makes it possible to define an analogue to the cooperation ratios for the response phase. To accomplish that we first reduce the number of classes of responder's options from 12 to six by disregarding information about the owners of the proposals. In other words, to classify options we will take into account the payoffs associated with the option and will not care if the option was proposed by first player to the second one or by the second player to the first one. Second, we will use the Page's rankings of the responder's options in the same way as we used the relative populations of the proposer's options. These two quantities have a different meaning. The populations of the proposer's options are determined by how frequently these options are chosen by the proposer while the Page's ranks of the responder's options are determined by how frequently these options are occupied in the jumping process used in the PageRank algorithm. Despite this difference these quantities still can be compared since they are both determined by the preferences of the player. The more attractive an option is, the higher its population is in the proposal phase and its Page's rank in the response phase. The reason why we cannot use the populations of different kinds of options given by the decisions of the responder (like we do for the proposal phase) is that in the response phase the populations are given not only by the preferences of the responder but also by the preferences of the proposers. For example, options of a certain type can be observed very rarely in the decisions of the responder just because they are rarely proposed by the proposer and not because they are not attractive to the responder.

We also have to mention that the preferences of the same player over the same set of options can be different for the two phases of the game. Even if we use the same parameters to measure the preferences and the number of games is large enough to have a good accuracy of this estimation, we can get some difference between the preferences of the players in the proposal and response phases. For example, it is a valid option that a player, being in the role of the proposer, prefers to propose helpful exchanges but in the response phase this player almost never accepts his/her own proposals and rejects the proposals of the partner if the latter asks for help. This inconsistency in the preferences of the same player in different phases can arise from the difference between how the player wants to position himself (for example, as a helpful person) and what he really wants to get from the game (for example to earn as many points as possible).

To compare the values of the level and symmetry of cooperation calculated for the two different phases of the game we have used the partner dependent populations and Page's ranks. For every player we have calculated two pairs of the cooperation ratios corresponding to two different partners. The data from the web-based experiment and Mars-500 experiment have been combined for this analysis. The correlations between the level and the symmetry of cooperation are shown in figure 7.13 and 7.14, respectively.

As we can see in these figures, the correlation between the values is not very high. However, we can also see a clear correlation between the two sets of values. To measure the correlation in a quantitative way the Pearson product-moment correlation coefficient has been calculated for the two ratios. The correlation coefficient for the level and the symmetry of cooperation calculated for different phases of the games is equal to 0.44 and 0.43, respectively. To determine how statistically significant these values are we have calculated the p-values of the null hypothesis assuming that there is no correlation between the ratios obtained for different phases of the game. In more detail, the ratios from the two different phases of the game were paired randomly so that a ratio calculated for one player from the proposal phase was paired with the ratio calculated for another player from the response phase. The correlation coefficients have been calculated for a considered random pairing of ratios and have been compared for the reference (real) correlation coefficients. The procedure has been repeated one million times and the portion of the cases in which the "fake" correlation coefficients were as high as, or even higher than, the real coefficient has been determined. This test has shown that, under the assumption of no correlation, the correlation coefficient can be as high as, or even higher than, the observed one only in 0.4% of cases (for both level and symmetry of cooperation). If we consider only the data from the Mars-500 experiment, the correlation between the levels of cooperation obtained for the two different phases of the game is even higher than for the data set including the data for the web-based experiment (it is equal to 0.60). However, since the data set from the Mars-500 experiment is smaller, the

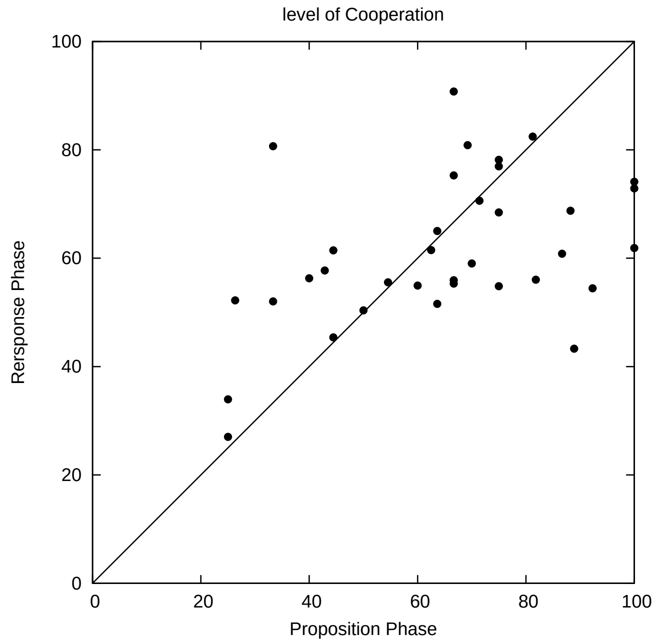

Fig. 7.13: Correlation between the values of the level of cooperation calculated for two different phases of the game

p-value of the null hypothesis, assuming that there is no correlation between the ratios from different phases, is also larger (it is equal to 0.028). The correlation between the symmetry of cooperation obtained for different phases within the Mars-500 experiment is only 0.31. Under the assumptions of the null hypothesis, the probability to obtain this number just by chance is equal to 0.18. However, taking into account the small values of the p-values for another ratio and for the extended data set we can conclude that the probability of the correlation between the ratios obtained for different phases of the game is very high. We also would like to emphasize that we have used the partner dependent cooperation level and symmetry of cooperation which are less accurate than the partner independent ratios. However, by using these numbers we were still able to find the results with high statistical significance. This means that even the partner dependent cooperation ratios are not just noise but parameters that provide a consistent (over different phases of the game) description of cooperative behavior of players.

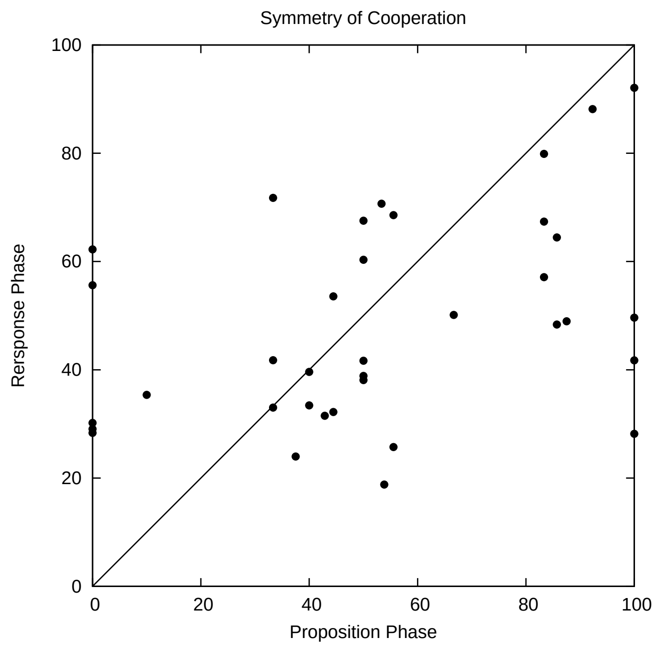

Fig. 7.14: Correlation between the values of the symmetry of cooperation calculated for two different phases of the game

8. FACIAL EXPRESSIONS RECOGNITION

The goal of this work is to develop a methodological toolbox for an automatic monitoring of psychosocial atmospheres during long-term missions performed by small crews in isolation. The first part of the thesis was focused on development of methods for analysis of the interactions between crew members in a gaming environment. The goal of the developed analysis of the interpersonal interactions is to derive insights about aspects of cooperation in interpersonal relations. The second group of tools in the toolbox should be focused on measuring and analyzing emotional states of the crew members because their interpersonal relations and emotional states are very tightly bound and influence each other. Moreover, healthy emotional states are as important for the success of the long-term missions as the interpersonal relations in the crew. To monitor emotional states in the crew 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. In this chapter we analyze the video records of the facial expressions made during the Mars-500 experiment. First, we discuss the general properties of the video record and the software that we used to automatically generate numerical data describing the facial expressions of the participants. Second, we present a simple classification of the statistical properties that can be calculated based on the data generated by the facial expression recognition software. We discuss the behavior of these properties and their meaning. In this section we also present two positive results. First, we report a memory effect observed for the collective emotional states, as revealed by the facial expressions, for the neighboring experiments separated by two weeks. Second, we demonstrate that there are relations of different types between the facial expressions of different users. We discuss how this relation can be calculated and used to characterize the strength and type of emotional binding between the crew members.

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8.1 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 minutes 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 [43] and playing the CT game [29] with each other. The frontal video records of facial expressions were made by the cameras located on the participants' computers.

8.2 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 [64]. The FaceReader software can recognize facial expressions by distinguishing six basic emotions (plus neutral) with accuracy of 89 % [64]. 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 [12]. For an overview of the progress in the field of automatic facial expressions recognition see [48, 14]. 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 milliseconds. 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.

8.3 Classification of Statistical Properties

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 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:

$$v(c,e,f) = \sum_u v(c,u,e,f), \tag{8.1}$$

$$v(c,u,f) = \sum_e v(c,u,e,f), \tag{8.2}$$

$$v(c,u,e) = \sum_f v(c,u,e,f), \tag{8.3}$$

$$v(c,u) = \sum_e \sum_f v(c,u,e,f), \tag{8.4}$$

$$v(c,e) = \sum_u \sum_f v(c,u,e,f), \tag{8.5}$$

$$v(c,f) = \sum_u \sum_e v(c,u,e,f), \tag{8.6}$$

$$v(c) = \sum_u \sum_e \sum_f v(c,u,e,f). \tag{8.7}$$

$$\tag{8.8}$$

8.4 Averaging over Users

Let us consider the introduced properties in more detail. The first property ($v(c,e,f)$) removes the dependency on users. For every given component of the facial expression, experiment and frame index we collect values corresponding to different users. After that, the six values corresponding to the six participants are averaged. As a result we get a measure that can be interpreted as a collective emotional state of the crew. The properties of this measure are more interesting to consider for a big crew, for which individual contributions from the users are suppressed by the averaging with contributions from other participants. Let us consider some examples of this property calculated with the available data. To calculate it we first find those parts of the experiments for which the facial expressions are categorized for as many users as possible. We found that there are no frames for which the facial expressions of all six users are categorized. The longest segment for which facial expressions of five users were categorized is only nine steps long. This segment is shown in figure 8.1. In the figure the happy component of the facial expressions of the 5 users is shown together with the happy component averaged over users. As we can see in the figure, the segment is not long enough to see any interesting dynamics.

To consider longer segments we found those parts of the experiment for which facial expressions of four users can be extracted at the same time. We found that the longest and the second longest segments with this property are 262 and 189 steps long, respectively. These segments are shown in figures 8.2 and 8.3, respectively. As we can see in these figures the averaged component is mostly determined by one of the contributions. The number of contributions is not large enough to make the averaging meaningful. The averaging could

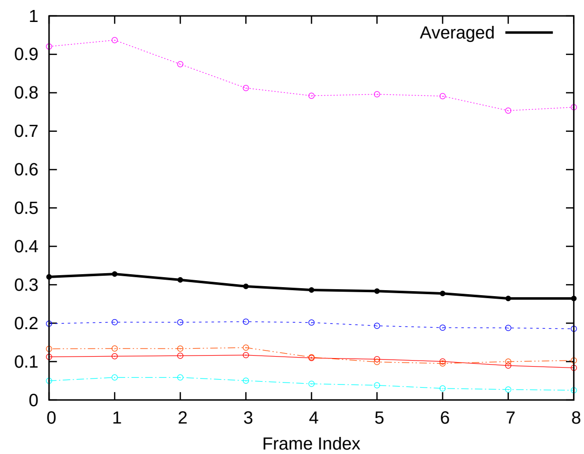

Fig. 8.1: The longest segment for which facial expressions of five users were extracted

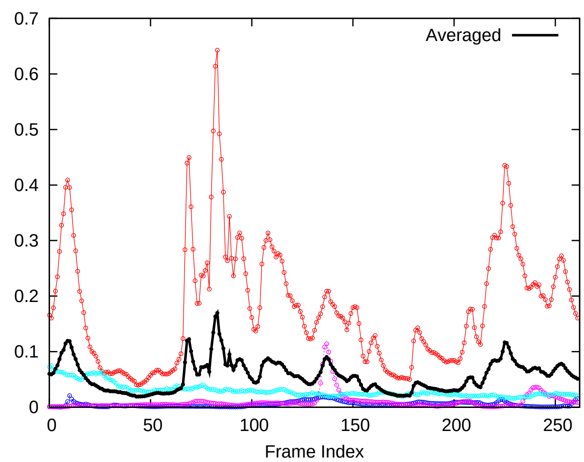

Fig. 8.2: The longest segment for which facial expressions of four users were extracted

be useful if the individual features disappear as a result of the averaging and, in this way, the analysis becomes simpler. However, in the considered case we have the opposite effect. The resulting curve contains features coming from different contributions, which makes the dependency more intricate than the original contributions.

8.5 Averaging over Experiments

The second introduced property $(v(c, u, f))$ removes the dependency on the experiment. To calculate this property we average all the values corresponding to different experiments but to the same user, frame index and component of the

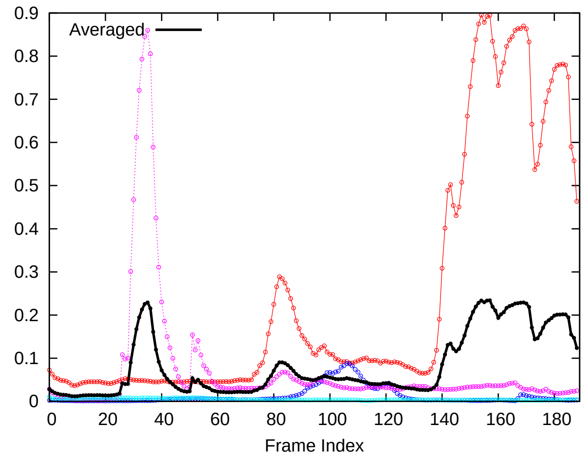

Fig. 8.3: The second longest segment for which facial expressions of four users were extracted

facial expression. As a result we get components of facial expressions depending on the users and the frame index. This property shows how the emotional state (facial expressions) of a given user depends on the duration of the experiment. If the experiment consists of different phases performed in the same order, then the considered property can be used to determine influence of these phases on the emotional states of the users. The number of experiments will determine the accuracy of the considered property.

The property $(v(c, u, f))$ is convenient to visualize as a function of the frame index (or duration of the experiment) for a fixed user and component of the facial expressions. Figures 8.4 and 8.5 show this dependency for neutral and happy components of the facial expressions of user 3, respectively. As we can see in the figures the shown dependencies (red lines) are quite noisy and there is no obvious regular dependency on the duration of the experiments. The nosiness of the data increases with the duration of the experiment. This behavior can be explained by the fact that the larger the time interval is, the smaller is the number of experiments that lasts so long. The number of available data points, divided by 10, as a function of the duration of the experiment is shown with the green line. As we can see from the figures, the number of available points decreases significantly between 20 and 25 minutes.

Trying to extract regularities from the noise we have calculated the average values of the components of the facial expression for every one-minute time interval. These values are also shown in figures 8.4 and 8.5 (see the black dots). The resulting dependencies are less noisy and we see that for different time intervals the average values are different. However, it is still unclear if these dependencies are real or they are still just noise. The question we are interested to answer is whether the difference between the average values corresponding to different time intervals is statistically significant. To answer this question we have calcu-

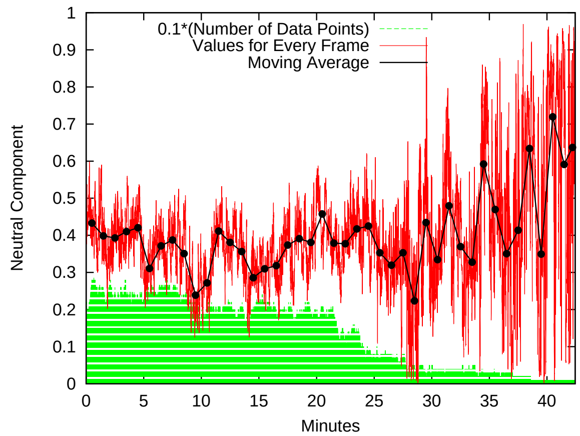

Fig. 8.4: Neutral component of the facial expressions of user 3 as function of the duration of experiment after averaging over all experiments

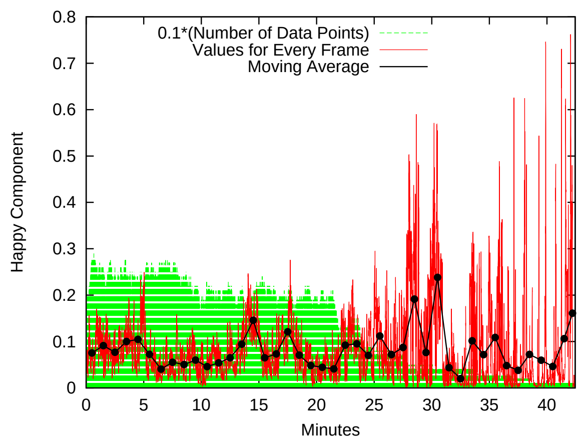

Fig. 8.5: Happy component of the facial expressions of user 3 as function of the duration of experiment after averaging over all experiments

lated the p-values of the null hypothesis assuming that values corresponding to any two one-minute intervals, separated by 10 minutes, are statistically indistinguishable. We make a loop over all experiments and for every experiment we extract the values of a given component of the facial expressions corresponding to the minute i and $i + 10$. The values from the two intervals are put into two different sets. The average values for the two sets are calculated and the difference between them is used as a measure of the difference between the two sets. Then we make another loop over all the experiments and, as before, we extract values corresponding to the interval i and $i + 10$. However, this time values corresponding to the minute i and $i + 10$ go to the wrong sets with probability of 0.5. In this way we construct two fake sets for which we calculate the averages and the difference between the averages. We repeat this procedure 1000 times to find out in how many cases the fake difference will be as large as, or even larger than, the reference distance. This will show how frequent the observed difference between the average values, corresponding to different one-minute intervals, can be as large as it is just by chance. The p-values calculated in this way are shown in figure 8.6 as function of i (the location of the first one-minute interval). The shown dependencies are obtained for the same user and the same

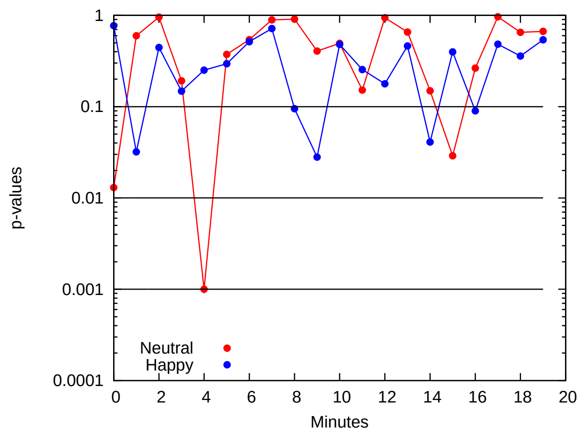

Fig. 8.6: The p-values of the null hypothesis assuming that facial expressions from two one-minute intervals, separated by 10 minutes, are statistically indistinguishable

components of his facial expressions as in figures 8.4 and 8.5. As we can see in figure 8.6, the p-values are too large to reject the null hypothesis. In other words, we do not have a good reason to say that the component of the facial expressions averaged over different experiments show a dependency on the duration of the experiments. The situation could be different in the case of larger number of participants or if the participants need to work with a program that has a stronger emotional influence that systematically depends on duration of the experiment.

8.6 Averaging over Frames

The third property $(v\,(c, u, e))$ removes the dependency on the time frame. In other words, 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 spent in isolation.

As an example, in figure 8.7 we show the dependence of the different components of the facial expressions (neutral, happy and sad) as functions of the experiment calculated for the third user. With the black histograms we show

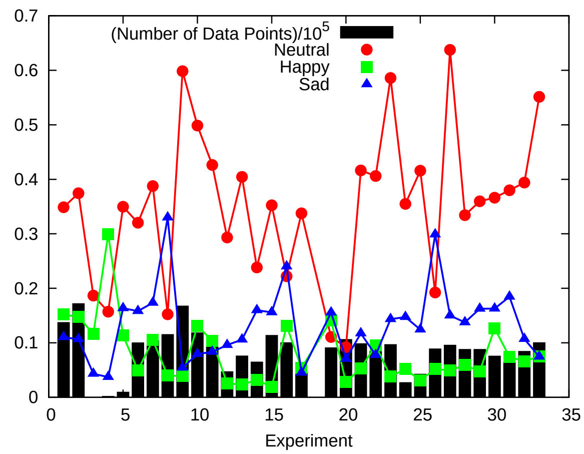

Fig. 8.7: Different components of the facial expressions of the third user as function of the experiment

the number of the available data points, divided by 10^5, as a function of the experiment.

In figure 8.7 we cannot see any obvious dependence on the experiment. 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 the 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. So, 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 distance between a pair of seven dimensional (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 numbers indicate that the used measure of regularity calculated for the dependencies shown in figure 8.7 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.

8.7 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 user 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 under no-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 figure 8.8.

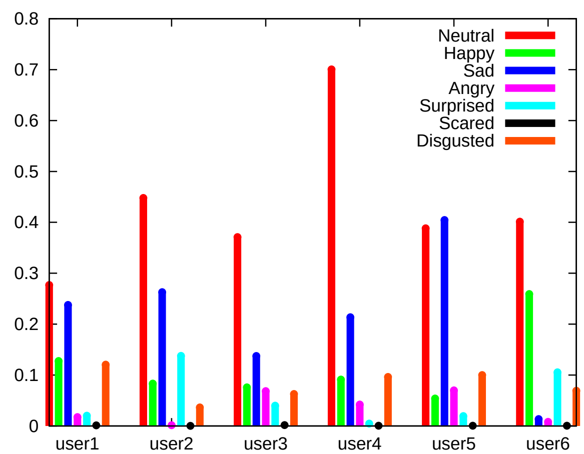

Fig. 8.8: Average values of seven different components of the facial expressions given for six participants of the Mars-500 experiment

8.8 Dependency on 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 figure 8.9. This figure is very similar to

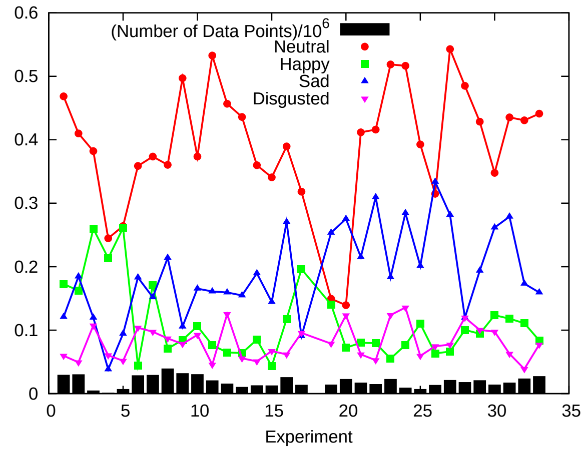

Fig. 8.9: Averaged (over frames and users) components of the facial expressions as functions of the experiment index

figure 8.7. The difference between figures 8.7 and 8.9 is that figure 8.9 shows the values averaged over all six users and figure 8.7 only shows values corresponding to user3. Moreover, in figure 8.9 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 $8 \cdot 10^{-4}$. So, 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.

8.9 Dependency on Frames

The sixth property ($v(c, f)$) is a result of the averaging over users and experiments. As a result, this property depends on the type of the facial expressions and frame index. In other words, it gives the average (over users) emotional state as a function of the frame index. This property is similar to the second property ($v(c, u, f)$); the only difference is that an additional averaging over users is performed in the second property. Similarly to the second property, the sixth property $(v(c, f))$ can be used to determine the emotional impact of different phases of the experiment on the participants.

This sixth property $(v\,(c, f))$ is shown in figure 8.10. As before, to reduce the

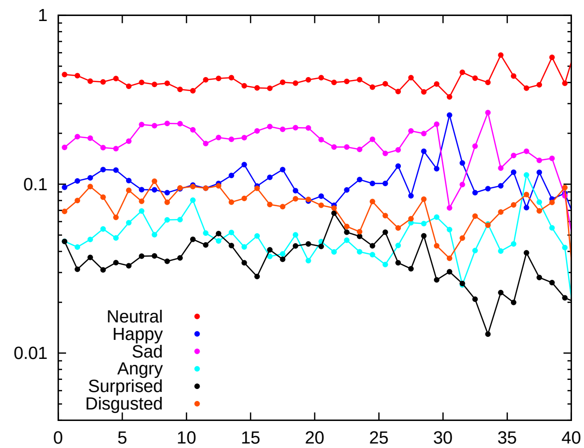

Fig. 8.10: Averaged (over users and experiments) components of the facial expressions as functions of the frame index

noise in the considered dependencies, we averaged the values over one-minute intervals. We did not show the "scared" component of the facial expressions since its values are extremely small; the average value of this component is only about 10^{-3}. We have also used a logarithmic scale to show all the components on one plot. As we can see in this figure the averaging over users makes the dependencies smoother (for comparison see figures 8.4 and 8.5).

We can conclude that the averaging over the users decreases the noise in the dependencies and, as a result, the dependencies can become more regular. However, on the other hand, we see that the values do not change so much as the frame index increases. To find out if there is some dependency of the considered properties on the frame index we have performed the same test as for the case of the dependencies obtained by the averaging of the facial expression over the experiments (shown in figures 8.4 and 8.5). As before, we have calculated the p-values of the null hypothesis assuming that the values corresponding to two one-minute intervals separated by 10 minutes are statistically independent. These p-values are shown in figure 8.11 as a function of the position of the first one-minute interval. As we can see in figure 8.11, the p-values of the null hypothesis are quite large for most of the pairs of one-minute intervals. Therefore, we can conclude that the difference between the values corresponding to different one-minute intervals is not statistically significant.

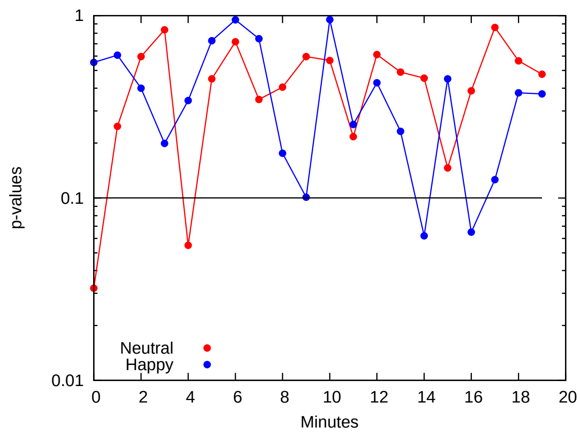

Fig. 8.11: The p-values of the null hypothesis assuming that facial expressions from two one-minute intervals, separated by 10 minutes, are statistically indistinguishable

8.10 Relation between Facial Expressions of Different Users

In this section we try to find a relation between the facial expressions of the participants of the Mars-500 experiment. A relation between the facial expressions of any two given participants can be caused by two different reasons. First, every participant interacts with his/her instance of the computer program and different instances of the program are synchronized. As a result, it can happen that some users simultaneously observe the same event and, therefore, they can have an emotional reaction on this event at the same time. Second, the participants can interact with each other through the provided computer program. In particular, within the CT game, the participants make proposals to each other and accept or reject proposals made by other participants. Moreover, the participants can communicate with each other using chats. This interaction between the participants can easily be accomplished with some emotions from both sides and we could expect that these emotions are related in some way. By an analysis of the relation between the facial expressions of different participants we can potentially determine how strong the emotional bonding between two given participants is. Moreover, we can expect that there could be different kind of relations reflecting different kinds of the emotional bonding between the participants. For example, we can determine if the second user is more likely to be happy if the first one is happy or, as an alternative, the users could tend to have opposite facial expressions at the same time (for example, the first user tends to be happy when the second user is sad).

To find a possible relation between the facial expressions of a given pair of users, we have considered joint 2D distributions of the different components of the facial expressions. In particular, to generate a joint 2D distribution we have paired the values of a given component of the facial expression for a given pair of users if these values corresponded to the same experiment and the same frame index. These pairs of values are then used to calculate a joint 2D distribution. If there is no relation between the facial expressions of the two given users, the obtained distributions should be independent. To compare the calculated joint distribution with the joint distribution for conditionally independent variables we have generated 2D distributions by a random pairing of the values corresponding to a given pair of users. In other words, in general cases the two randomly paired values correspond to different experiments and/or different frame index. It is clear that real joint distributions and a corresponding distribution for conditionally independent variables will be different just because of noise. Therefore, to make the comparison meaningful, we have estimated the statistical significance of the observed difference between the distributions. To do that we have calculated about 2,600 joint distributions of randomly paired values. Each of these distributions has been compared with the distribution obtained for the values that are paired according to their experiment and frame indices. For every grid on which the distributions have been calculated, we have calculated the number of times when the real joint distribution was larger, smaller or equal to the corresponding value of the distributions of the randomly paired values. We will denote these numbers as n_l, n_s and n_e, respectively. These numbers have been used to calculate the significance of the difference in the following way:

$$S(n_l, n_s, n_e) = \begin{cases} +1 \cdot (n_l + n_s + n_e + 1) \,/\, (n_s + 1) & if \quad n_l > n_s \\ -1 \cdot (n_l + n_s + n_e + 1) \,/\, (n_l + 1) & if \quad n_l < n_s \\ 0 & if \quad n_l = n_s \end{cases} \tag{8.9}$$

The meaning of this measure can be explained by the following example. Let us assume that for a considered grid the real joint distribution is larger than the distribution for conditionally independent variables for most of the cases. For example, in 998 out of 1000 cases the real distribution was larger than the distribution for conditionally independent variables and in two out of 1,000 cases it was smaller. So, we can say that only in one case out of 500 the real distribution was smaller than the distribution of independent variables. The number 500 can be used as a measure of statistical significance. The larger this number is the most statistically significant the difference is. In the above given example we needed to divide 1,000 by two. However, it can happen that instead of two we will get zero. To avoid the problem of division by zero we have slightly modified the measure. Instead of 1000/2 we use $(1000 + 1) \,/\, (2 + 1)$. The use of an additional 1 in the nominator and denominator should be insignificant for larger numbers of comparisons and it resolves the problem of division by zero. In addition to this modification we changed the sign of the measure from positive to negative if in most of the cases the real joint distribution is smaller than the distribution of independent variables. In this way by plotting the measure we can see not only how statistically significant the difference between the distributions is but also what the sign direction of the difference is.

The above described measure calculated for the neutral component of the facial expressions is shown in figure 8.12 for all 15 possible pairs of users. As

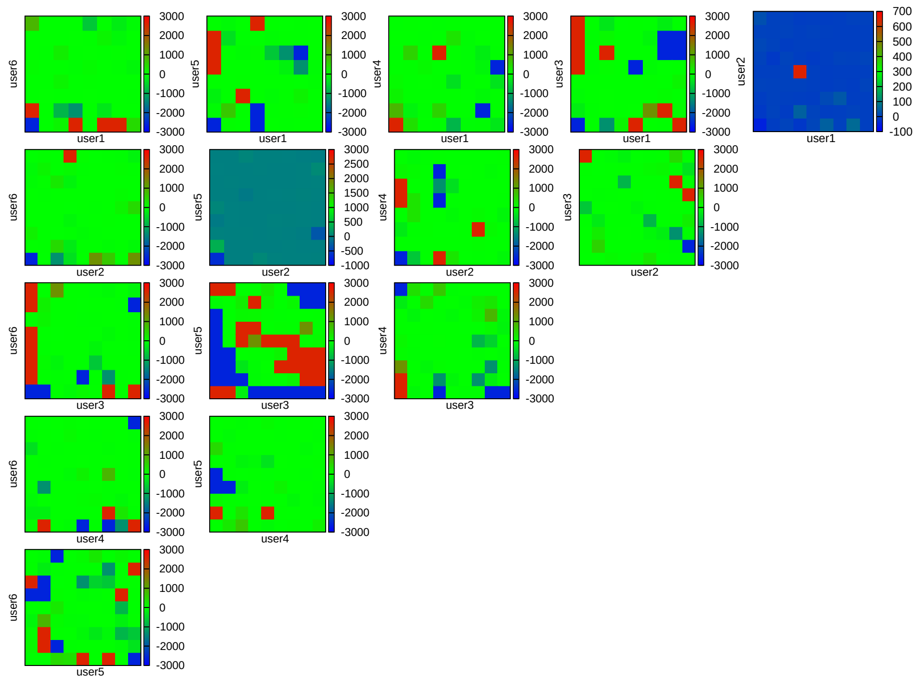

Fig. 8.12: Deviations of the joint distribution of the neutral component of the facial expression from uncorrelated distributions calculated for all possible pairs of users

we can see in the figure, there is no clear pattern that could be observed for all or even a majority of the users. Please note the pattern observed in the figure corresponding to user 3 and user 5. This pattern will be seen for other components of the facial expressions, and is also interesting because it has a clear interpretation. In the left bottom corner of the figure we see the red square, which means that if the first user has the neutral expression it is more likely that the second user also has the neutral expression. This effect is also supported by the blue squares along the two axes. The blue squares mean that the situations in which one of the users has the neutral facial expression and another one does not are less frequent than we could expect for unrelated facial expressions.

In the comparison made for the "happy" component we see the above described pattern even more (see figure 8.13). It is clearly seen for the two pairs out 15 (for user2-user3 and user3-user4). Something similar is also observed for the user5-user6 pairing.

This pattern was also found in the comparisons made for the case of the angry component (see figure 8.14). This pattern is clearly seen for three pairs of users: user3-user5, user3-user4, and user5-user6. In a weak form it is also seen for the user1-user3 pair.

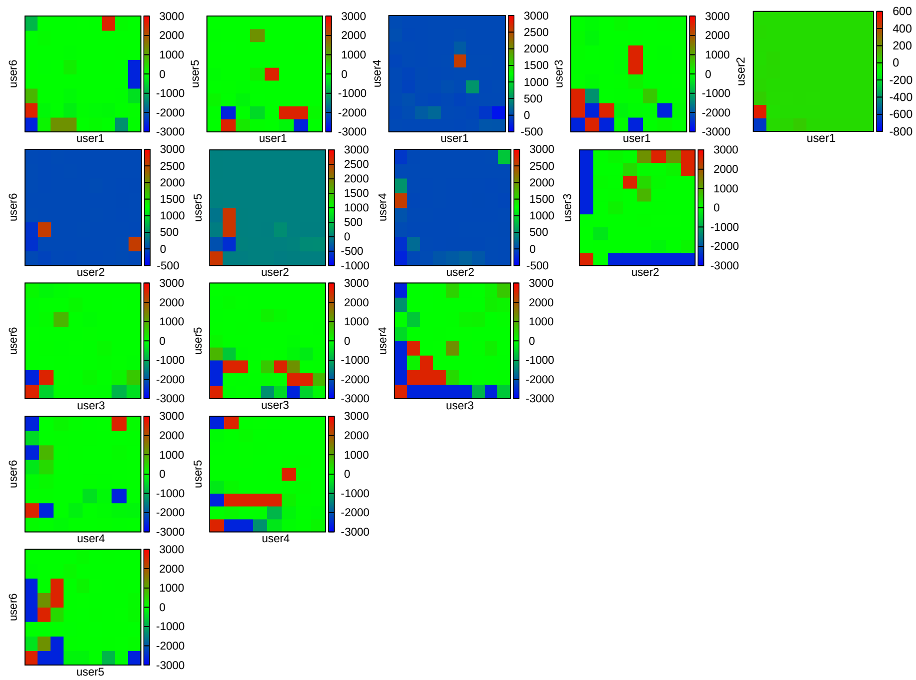

Fig. 8.13: Deviations of the joint distribution of the "happy" component of the facial expression from uncorrelated distributions calculated for all possible pairs of users

In case of the "surprised" component (see the figure 8.15), the considered pattern is clearly seen only for one pair of users: user3-user6. In a weak form it is present for another two pairs: user1-user3 and user4-user6. However, the "surprised" component of the facial expression is interesting because we can see another pattern that has an opposite meaning. This pattern can be clearly seen of the pair user3-user5. We see the blue square in the left bottom of the plot and the red squares close to the two axes. This pattern means that if one user is surprised it is more likely that another one will not be. A possible explanation of this relation between the "surprised" components of the facial expressions could be that in some cases one user surprises another one. As a consequence we have some moments when one user is surprised and another one is not.

The second pattern is observed even more frequently in case of the "disgusted" component of the facial expression (see figure 8.16). The second pattern is clearly seen for the following pairs of users: user1-user2, user1-user3, and user2-user3. In a weaker form the second pattern is also seen for two more pairs: user1-user4 and user3-user5.

To show more statistically significant results we have also considered joint distributions that combine the different components of the facial expressions. In other words, to get a real joint distribution for a given pair of users we

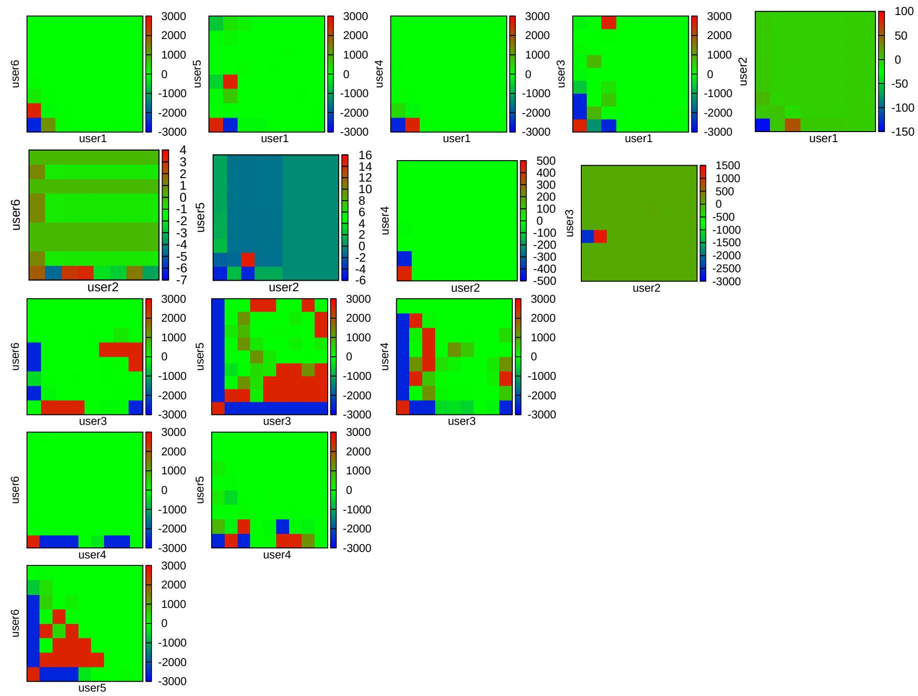

Fig. 8.14: Deviations of the joint distribution of the angry component of the facial expression from uncorrelated distributions calculated for all possible pairs of users

have paired the values corresponding to the same experiment, frame index and type of the component of the facial expression. In this way we get seven times more data points. For the combined consideration of different components of the facial expressions we have performed the same analysis as for the separate consideration described above. The measures of difference between the real distributions and distributions of unrelated variables are shown in figure 8.17. As we can see in the figure, the first pattern is even more pronounced in this case. This pattern means that the facial expressions of a considered pair of users tend to be similar at the same moment of time. In nine out of 15 cases the pattern is observed clearly and in three more cases the pattern is seen in a weaker form.

To summarize, we have presented a method of searching for relations between the facial expressions of different users. With the proposed method we saw that there is a relation for different components of the facial expressions. We have identified two opposite types of these relations. In the first case the users tend to have the same component of the facial expressions at the same time. In the second case certain expressions of one user decrease the probability that another user has the same expression. Potentially this method can be used to calculate the strength of the dependency between the facial expressions of different users.

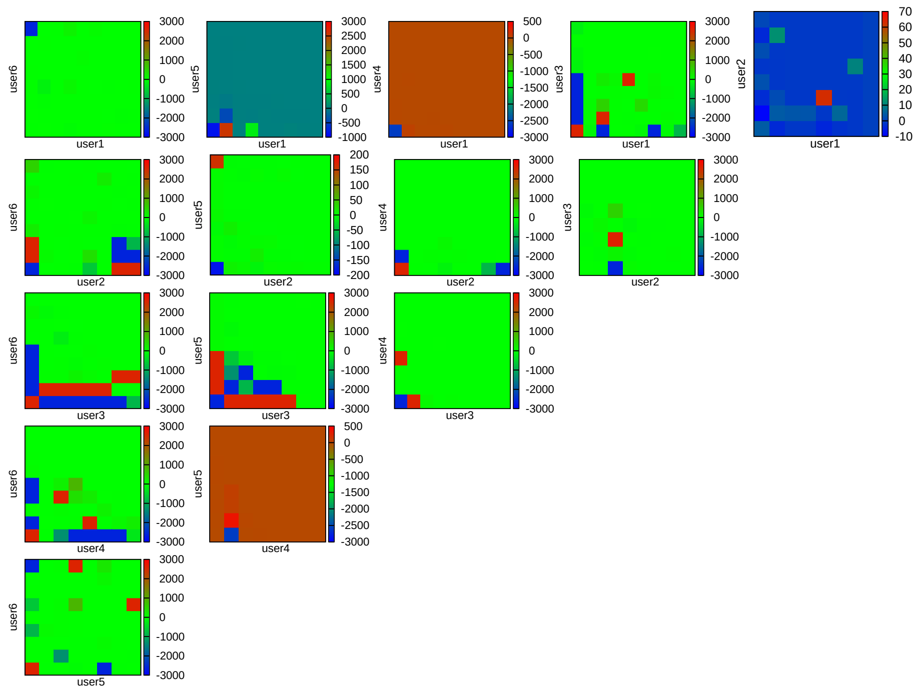

Fig. 8.15: Deviations of the joint distribution of the surprised component of the facial expression from uncorrelated distributions calculated for all possible pairs of users

Moreover, by analyzing the strength and the type of the relation for different components we can potentially discover different types of the relations between the facial expressions of different users.

8.11 Summary

In this chapter we have proposed several measures that can be used for analysis of the data generated by facial expressions recognition software. Using these measures we have found two positive results. First, we have found a statistically significant correlation between the average emotional states from two neighboring experiments separated by two weeks. Second, we have found two different types of relations between the facial expressions of crew members. The first result means that there is a slow component in the dynamics of the average emotional state of the crew so that two weeks cannot completely destroy memory about initial emotional state. This property of the dynamics of emotional states can potentially be used to predict emotional states of the crew for the next few weeks. Different types of relations between the facial expressions of different participants (the second finding) can potentially be used to describe types and intensities of emotional bindings between crew members.

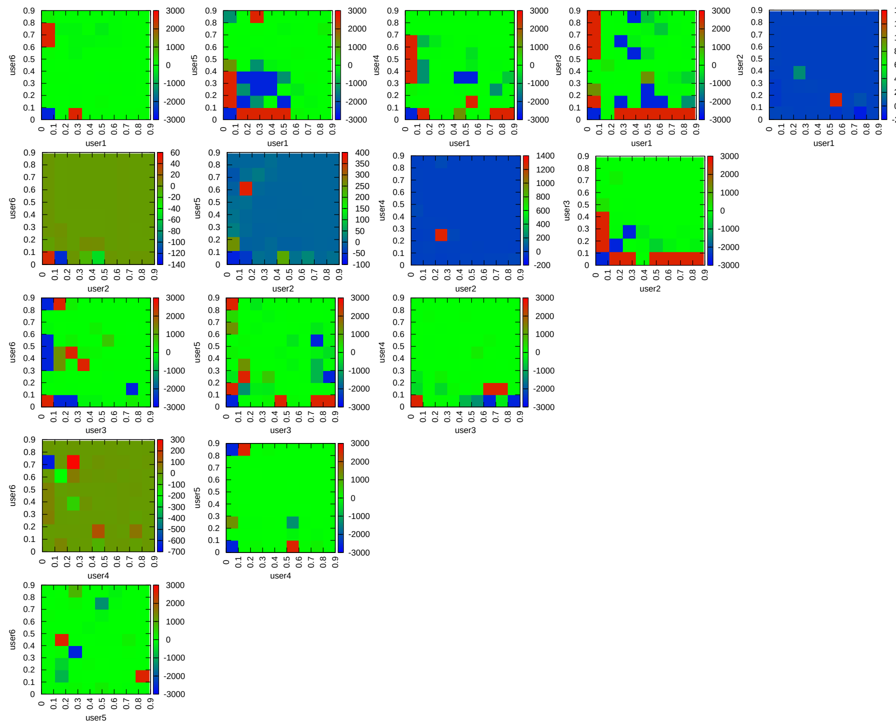

Fig. 8.16: Deviations of the joint distribution of the "disgusted" component of the facial expression from uncorrelated distributions calculated for all possible pairs of users

Another promising measure is the average emotional state of a given participant in a given experiment. This measure can potentially be used to monitor long-term effects on emotional states of the participant. Unfortunately, in our study we were not able to see any regularity in the values of this measure because of insufficient data. However, we believe that with more data it could be possible because we were able to see some regularity after averaging these measures over different users (the first finding). Using the available data and available software we were able to analyze only a small percentage of videos (less than 10%). This problem can be corrected by improving the quality of the video recordings (better lighting) or by improving the facial expressions recognition software.

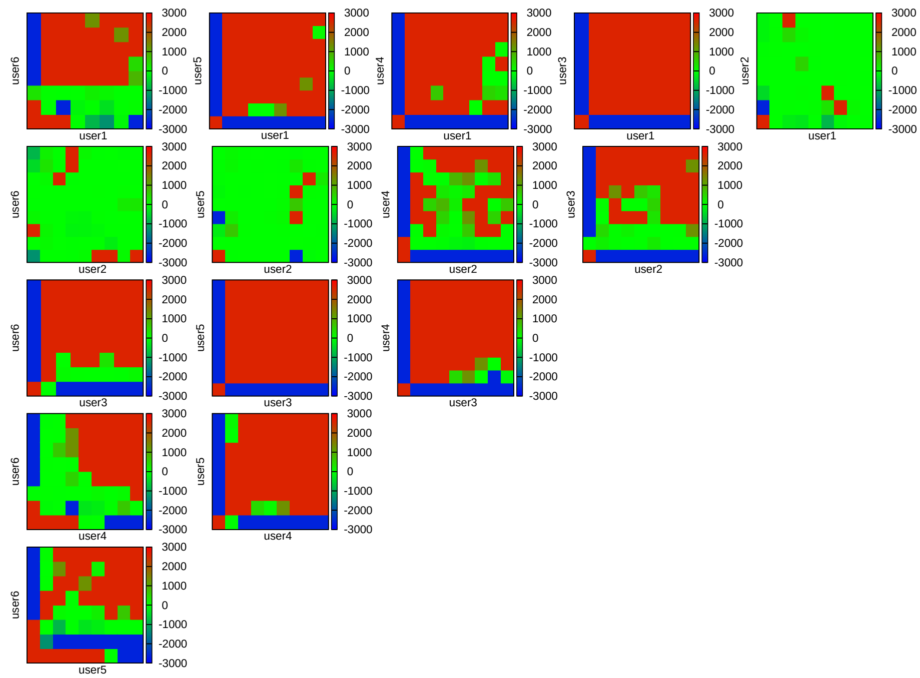

Fig. 8.17: Deviations of the joint distribution of the components of the facial expression from uncorrelated distributions calculated for all possible pairs of users

9. EMOTIONAL EVENTS

The previous chapter of the thesis is devoted to a descriptive (statistical) analysis of the time dependent parameters describing facial expressions. In this chapter we try to develop a model that focuses on the actual meaning of the time dependent facial expressions. In this way, we try to take a step to an interpretation of the observed dependencies. Specifically, we develop a model that is intended to explain the time dependent parameters of the facial expressions in terms of the emotional events. By emotional events we understand everything that causes emotions. The emotional events are assumed to be instant (they have no time duration). They differ from each other by type of the emotion that they cause (for example we can have "happy" or "sad" events). Moreover, every event is characterized by its intensity. For example an event can be very happy or a little sad.

Within the presented model, we assume that any facial expression at a given moment of time is determined by the following three factors: (1) type and strength of the last emotional event, (2) time separation between the current moment of time and location of the event and (3) the facial expression at the moment of the emotional event.

The main goal of this model is to interpret the facial expressions in terms of the event that caused them. In particular, the model should take the emotional events (their locations, types and intensities) as an input and generate time dependent parameters of the facial expressions as an output. With such a model we can also solve the reverse problem - the observed time dependent parameters describing facial expressions are taken as the input and as the output we generate emotional events given by their locations, types and intensities.

Transition from the time dependent parameters of the facial expressions to a set of emotional events should provide a reduced and more natural representation of the observed facial expressions. After this transition we can perform analysis of the data in terms of the statistical properties of the generated set of events. For example we can analyze frequency and/or intensity of "happy" events.

In this chapter we first describe the model in its simplest (linear) form and demonstrate how this model follows from the available data. Then we demonstrate how genetic programming and optimization can potentially be used to find a more general and more precise model.

The main goal of this chapter is to present the model and demonstrate how it can be improved by different optimization techniques.

9.1 Problem of Interpretation: Introduction

From an output of the applied facial expressions recognition software, applied to a video record, we get time dependent facial expressions given in terms of the basic emotions. Since emotional states experienced by a recorded subject can be very dynamic, the corresponding output can be quite complicated. In particular, the facial expressions in a state of transition from one pure expression to another one (*e.g.*, from "sad" to "happy") would be of specific interest for the analysis. We aim to find a method for interpreting the observed temporal history of facial expressions in the context of the events that caused the emotions. In this work we present a model that can help analyze and interpret output of facial expression recognition software. In particular we develop a model of emotional events that assumes that time dynamics of facial expressions are determined by events of different types and intensities and by facial expressions at the moment of the events. To find the way in which the facial expressions are determined by the events we use a genetic programming (GP) approach [4, 58]. Recently GP has produced many novel and outstanding results in areas such as quantum computing, electronic design, game playing, sorting, and searching, due to improvements in GP technology and the exponential growth in CPU power. The GP has been chosen among other optimization methods since it is oriented on a search of functions that fulfill certain criteria (and not on a search of a set of parameters). We therefore do not need to predefine the structure of the functional relation between the facial expressions and emotional events.

9.2 Model of Emotional Events

By emotional events we understand everything that influences emotions and, therefore, the facial expressions of participants. In other words, everything that makes participants happy, sad, scared *etc.*, is considered as an emotional event. In this section we propose a model that states that components of the facial expressions $\vec{f}_{k+i}$ are given by the last emotional event $\vec{s}_k$ and the facial expression at the moment of the event $\vec{f}_k$:

$$\vec{f}_{k+i} = \vec{F}\left(\vec{f}_k, \vec{s}_k, i\right). \tag{9.1}$$

In other words, we assume that after an emotional event the facial expression changes from the current state to the state corresponding to the emotional event. We will call the $\vec{F}$-function a response function because it determines the response of the facial expressions on emotional events. In the above expression (9.1) the lower indexes are used to numerate the time frames of the video. The k index gives the position of the last emotional event and the i is the number of time steps between the given facial expression and the moment when the last event happened.

In general the emotional events can be described through a set of parameters. This is the reason why we denote them as vectors: $\vec{s}$. In this work the emotional events are considered as two-dimensional vectors in which the first component indicates the type of an event (*e.g.*, "sad", "funny"), and the second component indicates its intensity (how "sad" or "funny" was it?). In this model an emotional event can be represented by its type t and intensity I. The type of the event is given by the type of the emotion that is provoked by this event. Hereafter we will use a terminology in which a "happy" or "sad" event is understood as an event that provokes feelings of happiness or sadness, respectively. In this notation the considered model can be written in the following form:

$$f^c_{k+i} = F^c\left(\vec{f}_k, t_k, I_k, i\right) = F^c_t\left(\vec{f}_k, I_k, i\right). \tag{9.2}$$

In the above equation we have also switched from the vector to an index notation. The upper index c is used to indicate different components of the facial expressions. In our model the parameter c ranges from 1 to 7, reflecting the fact that the FaceReader software uses seven numbers to quantify expressions.

By a preliminary observation of the available data we have found segments in which components of the facial expressions are smooth functions of time. An example of such segment is given in figure 9.1. By a further analysis of these

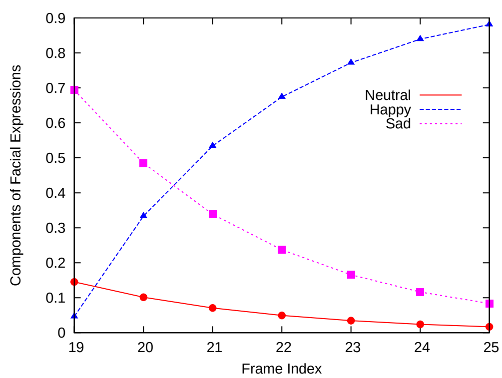

Fig. 9.1: An example of a segment in which components of facial expressions are given as smooth functions of time

patterns we found that changes of different components of facial expressions are linearly proportional to each other within a good approximation. In other words, from a geometrical point of view the considered segments lie on lines in the 7D space of the facial expressions. This fact is shown in figure 9.2. This property can also be given by the following mathematical expression:

$$f^c_{k+i} = f^c_k + \mu\,(i)\,(s^c_k - f^c_k)\,. \tag{9.3}$$

The function $\mu\,(i)$ should be equal to zero if $i = 0$ and be equal to one if i is large enough. In this case the facial expression starts to change from the expression at the moment of the event (f^c_k) and moves along a line to the final expression (s^c_k) corresponding to the given emotional event.

In addition to the above considered property in figure 9.2 we can see that linear parts of the dependencies form a pattern: all the lines are directed to

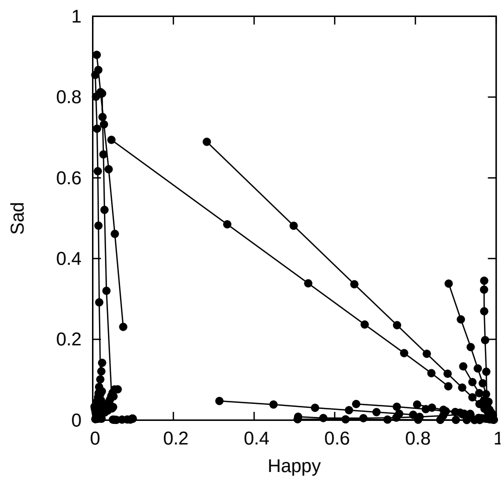

Fig. 9.2: Examples of the segments forming straight lines in the space of facial expressions

specific locations in the space of the facial expressions. For example, in the figure we can see two groups of lines that point to "happy" and "sad" facial expressions, respectively. Because of this property the mathematical expression for the dynamics of the components of facial expressions can be rewritten as:

$$f_{k+i}^{c} = f_k^c + \mu\left(i\right)\left(\delta_{tc} I_k - f_k^c\right), \tag{9.4}$$

where δ_{tc} is the Kronecker's delta. The t can be considered as the type of the event and I as its intensity. By fitting the observed dependencies we found that $\mu\left(i\right)$ can be approximated well by an exponential function $\mu\left(i\right) = \exp(-\alpha \cdot i)$. The equation (9.4) can be considered as a partial case of the above introduced general model (9.1). The expression (9.4) can be rewritten in the following form:

$$\begin{aligned} f_{k+i}^{c} = \quad & \delta_{tc}\{f_k^c\left[1-\mu\left(i\right)\right] + \mu\left(i\right) I_k\} + \\ & \left(1-\delta_{tc}\right)\{f_k^c\left[1-\mu\left(i\right)\right]\}. \end{aligned} \tag{9.5}$$

In the present study we use genetic programming to find the shape of the response function. To reduce the search space and, in this way, make the problem solvable we should restrict the form of the response function. In other words, we cannot search in a space of functions given by general expressions (9.1) or (9.2). On the other hand the structure of the response function should be able to capture not only the considered linear segments, given by the expression (9.5), but also more complex dependencies. As a compromise between these two extremes we will use a response function in the following form:

$$f_{k+i}^{c} = \delta_{tc} F_1\left(f_k^c, I_k, i\right) + \left(1-\delta_{tc}\right) F_2\left(f_k^c, I_k, i\right). \tag{9.6}$$

We would like to explicitly mention restrictions used in expression (9.6) as compared to the response function in the general form (9.2). As we can see, the response function in the form (9.2) is given by 49 functions corresponding to different values of c and t. In other word, by the expression (9.2) we specify how the "happy" component of the facial expression changes after a "sad" event, or how the "angry" component changes after a "happy" event and so on. In contrast, the expression (9.6) contains only two functions (F_1 and F_2). This restriction assumes that the way in which the i-th component of the facial expression is influenced by the i-th event is independent on i. In other word the "happy" component of the facial expression is assumed to depend on a "happy" event in the same way as the "sad" component depends on a "sad" event (assuming that the initial values of the components of the facial expressions and the intensities of the events were the same in the two mentioned cases). In the same way it is assumed that i-th component of the facial expression depends on j-th event in the same way for all possible combinations of i and j as soon as i is not equal to j. In other word the "happy" component of the facial expression is assumed to depend on a "sad" event in the same way as, for example, the "angry" component depends on a "disgusted" event. In particular, we assume that i-th component of the facial expressions decays after j-th event if i is not equal to j and the form of this decay is the same for all possible combinations of i and j.

9.3 Genetic Approach for Finding Response Functions

To find the functions F_1 and F_2 that determine the response of the facial expressions on emotional events of different types and intensities, we have used genetic programming.

In more detail, F_1 and F_2 have been represented as a tree. For example, the representation of the exponential functions corresponding to expression 9.5 are shown in figures 9.3 and 9.4. As nodes of the tree we used either basic functions

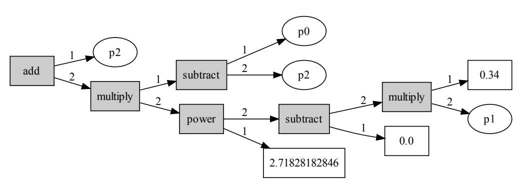

Fig. 9.3: Tree representation of the initial exponential guess for the first component (F_1) of the response function

or real constants or arguments. The set of the basic function consisted of seven functions: (1) addition, (2) subtraction and (3) multiplication functions of two arguments, (4) "if-function", (5) "greater-than-function", (6) power function and (7) arctangents. The "if-function" is a function of three arguments. It compares the first argument with zero, and if it is larger than zero the function returns the second argument. Otherwise the third argument is returned. The

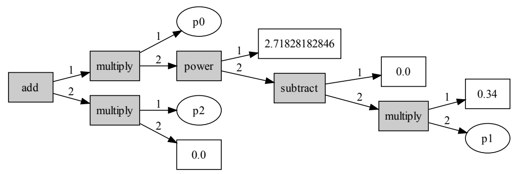

Fig. 9.4: Tree representation of the initial exponential guess for the fsecond component (F_2) of the response function

"greater-than-function" is a function of two arguments. It returns one if the first argument is larger than the second one. Otherwise the second argument is returned.

The functions F_1 and F_2 have three arguments. They are indicated in figures 9.3 and 9.4 as $p0$, $p1$ and $p2$. The first argument ($p0$) is the intensity of the event (I_k in the equation (9.6)). The k index indicates that this value is taken at the moment of the event. For example, in case of a "happy" event, $p0$ should be equal to the value of the "happy" component of the facial expression at the moment when the event was observed by the participant. The second argument ($p1$) is the number of frames between the current moment and the moment of the last emotional event (i in equation (9.6)). The third argument ($p2$) is the value of those component of the facial expression that correspond to the type of the emotional event (f_k^c in equation (9.6)).

To find a response function we have used a simple evolutionary process. The evolution started from the earlier defined pair of the exponential functions given by equation (9.5) and shown in figures 9.3 and 9.4. For the given pair of trees we have calculated a score that indicated how well the given pair of functions explains the observed dynamics of the facial expressions (more detail about the calculation of the score will be given later). Then we created a new pair of trees by mutation of every tree in the old pair. To mutate a tree we randomly choose a node in the tree and replaced it by a random tree. A random tree is generated in the following way. First we create a root node. We randomly decide if it should be a function or not. The probability for the node to be a function was set to 0.5. If a node is decided to be a function, then a function is randomly chosen from the earlier given list of the basic functions. If the node is decided not to be a function, then we decide if it should be a parameter (argument) or a constant. The probability for the node to be a parameter was set to 0.6. If a node is decided to be a parameter, one of the parameters is randomly chosen (either $p0$, or $p1$ or $p2$). If a node is decided to be a constant, a random number is generated and associated with the node. A random number generator with the uniform distribution between 0 and 1 was used. After a root node is created, we made a loop over its parameters (arguments) and generated nodes associated with them. The procedure is repeated recursively for every node in the tree whose child-nodes are not specified yet. The procedure is stopped if there are no nodes that require child nodes (constants- and parameters-nodes). The maximal depth of the tree was set to four to prevent generation of extremely large trees.

9.4 Training Set and Score Function

We have searched for the response function that could model not all the data but only segments around the patterns described earlier and shown in figures 9.1 and 9.2. To find a generalization of dependency 9.5 we have extended the linear segments by preceding and subsequent steps of the data. The addition of nonlinear segments requires the use of a more general function. To find this function we have used GP techniques. Specifically, we have selected all the parts of the trajectories in the space of the facial expression that lie on a line. In particular, the points were considered as lying on a line if the angle between the line connecting the first and second points and the line connecting the second and third points was not larger than three degrees. Three video records have been considered. The number of segments with the above described properties in these records was 26, 52 and 21 respectively. The minimal and maximal length of the segments was six and 12 steps, respectively. The average length of the segments was equal to 7.3 steps. To capture patterns happening immediately before and after the considered segments we have added to them 20 preceding and 31 subsequent steps.

For every extended segment we have searched for the best emotional event that could explain the dependencies observed in the segment. Specifically, we made a loop over all possible locations, types and intensities of the event. The loop over intensities of the events was run from 0.0 to 1.0 with the step equal to 0.01. For every considered event we used the available response function to predict the dynamic of the facial expressions. First we combined the intensity and type of the event with the facial expressions at the moment of the event to estimate the facial expression on the next step. Then the difference between the estimated and observed facial expression has been calculated. In particular, the estimated and real (observed) facial expressions can be represented as points in the 7D space of the facial expressions. As a measure of the difference between the estimated and observed facial expressions we have used the distance between the two points, representing the two kinds of the facial expressions, divided by the average length of the vectors connecting the origin of the coordinate system and the two points:

$$d = 2\frac{|\vec{o} - \vec{p}|}{|\vec{o} + \vec{p}|}, \tag{9.7}$$

where $\vec{o}$ and $\vec{p}$ are the observed and predicted facial expressions. The predicted facial expression has been considered as accepted if its deviation from the observed expression has been smaller than 0.03 according to measure (9.7). After the prediction for the given step was accepted, a prediction for the next step was generated and evaluated in the same way. The procedure was repeated until an unaccepted prediction is reached. Then the total length of the prediction was calculated. In this way we get a location, type and intensity of the event that maximize the length of the prediction for the considered segment. This procedure was performed for all the segments with a given response function and the total length of the predictions has been used as a measure of the quality of the considered response function.

9.5 Optimization Procedure

We started the evolutionary process from the response function given by expression (9.5) and shown in figures 9.3 and 9.4. Then we generate new response functions and evaluate their scores until a function with a score larger than or equal to those of the initial function is found. The new response function then replaces the initial function and the whole procedure is repeated. The procedure is stopped if the score has no improvement for a large enough number of generations.

After the evolutionary search is stopped we run a hill climbing optimization algorithm to find new values for the constants involved in the trees to improve the predictive power of the response function. We make an iteration over all constants in the pair of trees. For every constant we consider the two neighboring values separated by 0.1 from its original value. Then we choose the variable and the direction of the shift over this variable that maximize the predictive power of the response function. If no improvement is possible we decrease the current step by 1.1.

We have run three independent optimization procedures for three different video records. After that the response functions optimized on the three independent sets of data were tested on the data that were not used during the optimization.

9.6 Response Function

We have run the evolutionary optimization procedure for three video records. These optimization procedures have been manually stopped after 2165, 156 and 672 steps of the evolution, respectively, because the score did not improve for several hundred steps. In all three cases we got an improvement of the predictive power of the response function if compared with the initial exponential guess given by the equation (9.5). Specifically, the average length of the accepted prediction made with the initial exponential guess was equal to 10.15, 10.98 and 10.48 steps for the three video records, respectively. After the evolutionary optimization the predictive power increased up to 12.50, 12.85 and 12.29 steps, respectively. The additional hill climbing optimization of the response functions found in the evolutionary optimization also led to an increase of the predictive power of the response functions in all three cases. However, the improvement was very small. After the hill climbing optimization the predictive power in the three cases increased to 12.65, 13.46 and 12.38 steps. These results are summarized in table 9.1.

Tab. 9.1: Average length of the predictions for different data sets and response functions.

	Video 1	Video 2	Video 3
Initial Guess	10.15	10.98	10.48
After Ev. Opt.	12.50	12.85	12.29
After H. C. Opt.	12.65	13.46	12.38

The examples of the found response functions are shown figure 9.5 and 9.6.

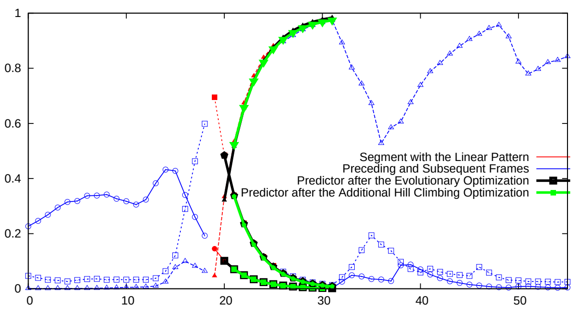

Fig. 9.5: An example of the first response function representing different components of the facial expressions

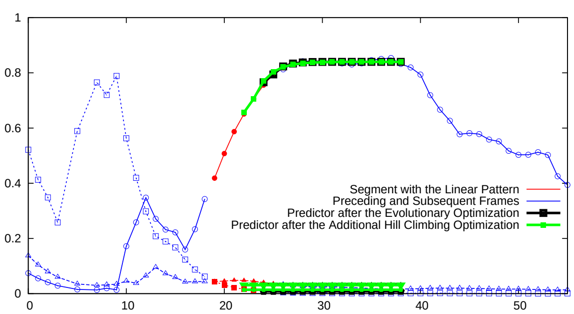

Fig. 9.6: An example of the second response function representing different components of the facial expressions

To make sure that we do not have an overfitting effect, the response functions were tested on the data that were not used in the optimization procedures. The results of this test are summarized in table 9.2. As we can see in this table, the first response function, which was obtained with the first video record, performs well for the second and third video records. The average lengths of the prediction for the second and third video records are even larger than those for the first one. Moreover, the considered response function has a higher predictive power for the third video record than the third response function that was obtained with this record. So, we can conclude that the first response function has not been

Tab. 9.2: Cross validation of the response functions.

	Video 1	Video 2	Video 3
No Opt.	10.15	10.98	10.48
R.F.1	12.65	12.92	13.24
R.F.2	10.31	13.46	11.86
R.F.3	10.35	13.08	12.38

overfitted. The second response function performs best for the second video record and has a low predictive power for the other two records. However, even for these two records the predictive power of the considered response function is larger than those of the exponential response function used as the initial guess. The third response function, obtained with the third video, also performs well with the second record but not so well with the first one. As a general conclusion we can say that response functions obtained just with one video record are meaningful and could perform well for other records. However, a small effect of the overfitting is present and for further optimization of the response functions it is recommended to use a larger set of data.

10. CONCLUSIONS

Cooperation among people in teams that are bound to perform a common goal is one of the main factors determining success of these teams. Cooperation becomes even more important for small teams performing long-term missions in isolation. Examples of such missions include missions performed on the international space stations, polar research stations, submarines, oil platforms and meteorological stations. Such missions are usually performed in extreme physical and psychological conditions that have a strong negative effect on emotional states of the crew members and interpersonal relationships between them. In this work we develop a set of methods for an automatic measuring of cooperative behavior and emotional states in goal-oriented teams performing long-term missions in isolation. The proposed methods were tested on and applied to data from the Mars-500 isolation experiment. The methods are based on analysis of two kinds of data: behavior in a cooperative computer game and video records of facial expressions.

In particular, in our study we used the CT game to be a research testbed for investigating decision-making in groups comprising people, computer agents, and a mix of these two. In our work we proposed to use the CT game with specially designed payoff spaces that make it easier to tie decisions of the players in the game with the social preferences of the players. To describe cooperative behavior of players in the proposal phase of the game two ratios were introduced. The first ratio, called level of cooperation, is used to describe preferences of each player over cooperation and fairness. The second ratio, called symmetry of cooperation, describes difference between sacrificing and exploiting behavior of players. The introduced ratios provide a quantitative way to describe cooperative behavior of players in the game. In this work we demonstrated that different players behave differently in terms of the introduced ratios. Moreover, the behavior of a player can depend on who his/her opponent is in the game. In this way we demonstrated that cooperative games can be used to capture some cooperative aspects of interpersonal relationships between different players.

In addition, we proposed a utility function that describes cooperation and different kinds of fairness. To derive this utility function we started from building a link between the social-welfare and inequity-aversion utility functions that are well established in literature. Moreover, we considered the way in which these functions are generalized to the case of more-than-two subjects and proposed an alternative generalization procedure. Finally, we extended the utility function by adding a term that models an additional type of fairness. For the case of two players, the introduced utility function contains three parameters describing the players' social preferences. The utility-based approach can be considered as a more general than the approach based on the use of cooperation ratios because the two cooperation ratios can be obtained from the values of the three utility parameters but the opposite is not true.

Influence of the combinatorial complexity of the game on the decisions of the players has been considered to develop a model that can explain non optimal decisions of the players in the game. Three parameters that determine combinatorial complexity of the decisions in the game were identified and their influence on the decisions of each player has been demonstrated. To find correct values of the utility parameters, describing social preferences of a player, we need to take into account the fact that the ability of players to find options in the game is limited by the combinatorial complexity of the game. To do that, we proposed different measures of inconsistency between a given set of utility parameters and a given set of decisions. We demonstrated that a correct choice of a measure of inconsistency is very important for the proper estimation of the utility parameters. Moreover, we proposed a model-based approach to the construction of the inconsistency measures and demonstrated that this approach provides a better way to estimate the utility parameters of the players.

The social preferences of the players revealed in the response phase of the game were described by a network of player's preferences over different types of proposals. Different ways to quantify these preferences were proposed. A link between the methods, developed for the proposal and response phases of the game has been made and, in this way, it has been demonstrated that the parameters calculated for the different phases and describing social preferences of the players are in a statistically significant agreement.

Finally, we analyzed video records of facial expressions taken during the experiment. For the analysis of the facial expressions we considered different statistical properties, provided their classification and described their meaning. By considering these properties we found two interesting results. First, there is a statistically significant correlation between the emotional states of the crew for the neighboring experiments (separated by two weeks). Second, we found different types of the relations between the facial expressions of different users. We discuss a possibility to use these relations as quantitative measures of emotional bonding of different types and strengths. In addition to the use of the statistical properties we developed a mathematical model that could help to interpret time-dependent facial expressions in terms of events inducing emotions. With the proposed method we can find the locations of these events in time as well as the type and value of the impact that they have on emotional states.

In summary, we proposed a methodological toolbox for an automatic monitoring of the psychosocial atmosphere in small groups performing long-term missions in isolation. We studied the possibility to use computer games to monitor interaction between crew members and, in this way, access some aspects of their interpersonal relations. Special attention has been paid to cooperative aspects of interpersonal relations. To monitor emotional states of the crew members we utilized the progress made in the field of automatic facial expressions recognition and focus on the method of analysis of facial expressions, which are relevant to the monitoring of interpersonal relations and long-term effects of isolation.

This work can be considered as a first step in the development of systems for an automatic monitoring of psychosocial atmosphere in goal-oriented teams. A lot of additional research and testing has to be done before a comprehensive system of this kind can be created. Further progress in this area would involve the following: First, the games used for a monitoring of interactions between the crew members have to be made gradually more and more rich in terms of the decision making situations to capture different aspects of interpersonal relations. Any extension of the games has to be supported by a development of theories for analysis and interpretation of the playing behavior in the extended settings. Second, the combinatorial complexity of the game has to be decreased to decrease the time needed for making decisions and, in this way, increase the number of decisions (data for analysis) per game. Moreover, reduction of the combinatorial complexity can help to separate effects of social preferences from the effects of complexity.

For a more comprehensive monitoring of emotional states, measurements of voice intonations look very promising since humans are shown to express their emotions through facial expression *and* voice intonation. Moreover, usually people express their emotions through voice intonation during their communication with each other. This aspect can be very interesting in the context of monitoring interpersonal relations.

Finally, a progress in the development of tools for an automatic facial expression recognition and voice intonation interpretation can be accomplished by the development of methods for analysis of the data generated by these tools. In other words, we need models that can bind the observed (and classified) facial expressions and voice intonations with underlying psychological processes in a deeper way.

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11. APPENDIX

11.1 Evolutionary Approach to Generation of Games

As described in chapter 2.4 we want to use the games in which the sets of the payoff options, corresponding to different predefined strategies, do not overlap with each other. This property allows us to derive a strategy from the decisions of the players. We have found that only a very small percentage of the games have the above mentioned property. A random search for the games with this property would be too time-consuming. To overcome this problem an evolutionary search was performed. In particular, we started from a randomly generated game. The state of the field, the positions of players and the goal as well as redistribution of chips was done randomly. The only restriction we applied is that every player can have from three to five chips. Then we started an iterative process in which the state of the field, the position of the player, the location of the goal, or the set of chips was modified. During the modification of the field we randomly changed the color of a randomly chosen square. Changing a position of a player or of the goal we made one horizontal or vertical step to one of the neighboring squares (under the obvious restriction that elements of the game should stay on the field). In addition, we did not allow two players to occupy the same square. By modifying a set of chips we randomly chose a player and added or removed a chip of a randomly chosen color. By doing that we held the restriction that the number of chips owned by one player should be between three and five.

On every step we calculated the overlap between sets of options representing different strategies. The size of the overlap was calculated for every potential pair of players and the total size of the overlap was taken into account. In this way we could guaranty that the game will be interesting independent of who negotiates with whom. A considered mutation was accepted only if it decreased the overlap. The mutation process was continued until no overlaps were found for any pair of players.

11.2 Generalized Probabilistic Model of Horizon

In chapter 6.3 we presented a simple model of horizon that takes into account the fact that players do not always notice all options available in the game.

There is another simple model that we will introduce for completeness. Within this model we assume that every option has the same probability ν

to be noticed. Let us calculate the probability that a given option will be proposed, as follows. As in the section 6.3 we will use the h- and l-subsets of options. Within the considered model the given option will be proposed only if all the options from the h-subset are not noticed and the given option is noticed. In other words, we assume that the player proposes the option that has the highest utility among the options from the set of noticed options. For every option the probability to be unnoticed is equal to $1 - \nu$. As a consequence, the probability that all the options from the h-subset are unnoticed is equal to:

$$P(h, l) = (1 - \nu)^h . \tag{11.1}$$

This probability should be multiplied by the probability that the given option is noticed ν. As a result, we get the probability that the given option will be proposed:

$$P(h, l) = \nu (1 - \nu)^h . \tag{11.2}$$

The found probability depends on the parameter ν of the model and on the position of the option in the list of the options ordered by their utilities.

The derived probability can be used as a measure of disagreement between the assumed utility and a given decision (proposed option). In other words, the probability that the given (proposed) option will be proposed depends on the utility of the player. Therefore, we can search the utility parameters that maximize this probability. In case we have several decisions from several games, we can use the probability that the given sequence of the decisions will be observed given a set of utility parameters. The probability of a sequence of decisions is just a product of the probabilities of every decision. As we can see, even a simple a model of horizon naturally provides a measure of disagreement between the assumed utility and a given set of decisions.

We have introduced the two simple models capturing the fact that some options can be hidden by the combinatorial complexity of the game. Both models are simple and do not bind the probability of an option to be noticed with the parameters of the option. There is no *apriori* knowledge that could help us to choose between the two above defined models. Moreover, it can be that the real behavior of the players is more complex than those assumed by the two models and a combination of the two models can provide a more realistic description of the observed data. For this reason we define a more general model that contains the two earlier defined models as partial cases and let the data determine to what extent each of the partial cases should contribute to the description of the observed data.

In the first partial case we assume that every option can be noticed with the same probability ν. In the second partial cases we assume that there are r options for which the probability to be noticed is equal to 1 and for the rest of the options the probability to be noticed is equal to 0. As a generalization of these models we can assume that, like in the second partial case, all the available options are split into two subsets: r-subset and the rest. However, for the options from the r-set the probability to be noticed is equal not to 1 but ν_b and for the remaining options the probability to be noticed is not 0 but

ν_s. So, the general model is given by three parameters: r, ν_b and ν_s while the original two partial cases are given just by one parameter ν and r. It is easy to see that if $\nu_b = \nu_s = \nu$, the difference between options from the r-set and the rest disappears (the options from the two sets have the same probability to be noticed) and, accordingly, we will get the first partial case. The second partial case is obtained if $\nu_b = 1$ and $\nu_s = 1$.

Let us calculate the probability that a given option will be proposed assuming the above described generalized model. As before, for the given option to be proposed the two conditions should be fulfilled: (1) the given option should be noticed and (2) all the options with the higher utilities (options from the h-set) should be unnoticed. There are two possible mutually exclusive scenarios: (1) the noticed option belongs to the r-set and (2) the noticed option does not belong to the r-set. We will calculate the probability of every scenario and then the probability that a given option will be noticed will be given as the sum of the probabilities of the two scenarios.

The probability that the given option belongs to the r-subset and is noticed is given by the following expression:

$$P = \nu_b \cdot \frac{r}{h+l+1}. \tag{11.3}$$

To get the probability that the given option is from the r-set and is proposed we have to multiply the above probability by the probability that all the options with the higher utility (options from the h-subset) are not noticed. The probability that none of the h-options is noticed depends on the number of the r-options in the h-subset, since options from the r-subset have a higher probability to be noticed. So, let us calculate the probability that there are i r-options in the h-subset. We have done it already for $i = 0$. In total there are C_{h+l+1}^{r-1} ways to choose $r-1$ options from the $h+l$ options. Among all the possible ways to choose $r-1$ options out of $h+l$ options we need to calculate the portion of those way for which there are i options in the h-subset and $r-i$ options in the l-subset. There are C_h^i ways to choose i options out of the h option and C_l^{r-1-i} ways to choose $r-1-i$ options out of the l options. Combining all that we can say that the probability that there will be i options in the h-set is equal to:

$$\frac{C_h^i C_l^{r-1-i}}{C_{h+l}^{r-1}}. \tag{11.4}$$

So, we can say that the probability that the given option will be in the r-set and it will be proposed is equal to:

$$P = \nu_b \cdot \frac{r}{h+l+1} \sum_{i=0}^{r-1} \frac{C_h^i C_l^{r-1-i}}{C_{h+l}^{r-1}}. \tag{11.5}$$

To calculate the probability that the given option will be proposed we should also consider the case when the given option does not belong to the r-set. The probability that a random option is not in the r-set is equal to $(h+l+1-$

$r)/(h+l+1)$. For such an option, the probability to be noticed is equal to ν_s. So, for an option the probability both to be from the r-set and be noticed is equal to:

$$p_n = \nu_s \cdot \frac{h+l+1-r}{h+l+1}. \tag{11.6}$$

Now we also need to calculate the probability that none of the options from the h-subset is noticed. For that we can use the expressions that we got before. We just need to remember that there are r options from the r-subset among h- and l-subsets (and not $r-1$ as before). This is because for the considered case the given option does not belong to the r-subset. In this way we get the following expressions for the probability that the given option will be proposed:

$$P = \nu_b \cdot \frac{r}{h+l+1} \sum_{i=0}^{r-1} \frac{C_h^i C_l^{r-1-i}}{C_{h+l}^{r-1}} + \nu_s \cdot \frac{h+l+1-r}{h+l+1} \sum_{i=0}^{r} \frac{C_h^i C_l^{r-i}}{C_{h+l}^{r}}. \tag{11.7}$$

The above expression combines decisions of a given player in a given game, three utility parameters and three parameters of the model of noticing (r, ν_b and ν_s). The utility parameters do not enter the expression explicitly. However, they determine the utility of every option and, as a result, the sizes of the l- and h-sets (*i.e.*, the considered expression depends on the utility parameters through l and h). As a result, the expression returns the probability that a given decision will be proposed given the assumed parameters of the model and utility parameters. Multiplying the probability corresponding to every decision (game) we will get the probability of a given sequence of decisions. By maximizing this probability we can find the most likely utilities of the given player and the most likely values of the parameters specifying the model of noticing. The found utility parameters can be used to describe the social preferences of the given player (*i.e.*, how much he/she cares about cooperation and different types of fairness). Another potential use of the considered expression is an estimation of mental fatigue. This use of the parameters of the model assumes that a person can notice less options if he/she is more tired.

11.3 Comparison of Decisions

The decisions made in the game can depend on many factors such as:

- Who is the decision maker?
- Who can be affected by the decision (for example, who is the partner in the exchange)? What are relationships between the decision-maker and the subject who can be potentially affected by the decision?
- When is the decision made? The decisions can be dependent on time because of many factors such as psychological state and interpersonal relationships.

We need to find an appropriate way to estimate if a given factor influences the decision-making process. For this purpose we have developed the following general approach. For a given set of decisions we need to specify a set of parameters that describe these decisions and that can be affected by the factors of interest. As an example we can mention several choices of the parameters describing a set of decisions:

- Cooperation ratio and give/take ratios.
- Average and RMSD of the angles of the benefit.
- Three utility parameters.

The parameters describing a set of decisions can be represented as a point in an N-dimensional space (where N is number of parameters). Then the difference between two sets of decisions can be measured as the distance between the corresponding two points in the parameters space. We use the obtained distance to estimate the probability that the observed (or large) distance can be observed provided that the given two sets of decisions are statistically indistinguishable (our null hypothesis). If it is very unlikely to observe such a large (or larger) distance, given the assumed null hypothesis, we can conclude that the null hypothesis is very likely to be wrong. In other words, we can conclude that the given two sets of decisions are statistically distinguishable.

Let us assume that we have two sets of decisions. We calculate the distance between the two sets (the "reference" distance). Then we assume that the two given sets were generated by the same decision making algorithm. Now we want to estimate the probability that such a large, or larger, distance can be observed given our null hypothesis. To estimate this probability we mix and shuffle the two sets and split them into two "fake" subsets whose sizes are equal to those of the two original subsets. For the two "fake" subsets we calculate the distance which we will call the "fake" distance. Since the common set was split randomly than the "fake" distance can be considered as "noise" or "fluctuation" (something that happens just by chance). We compare the described procedure many times to get many fake distances that are then compared with the reference distance. In this way we can estimate the probability that the observed reference distance can be so large (or larger) just by chance.

For one pair of compared sets the null hypothesis can be considered as wrong if the reference distance is larger than the vast majority of the fake distances. However the statistical difference between the two sets and the sizes of the sets can be too small to see an appreciable effect. In this case the situation can be improved if we compare many pairs of sets. For example, it might happen that we do not see a convincing difference between the proposals of the same player made to different partners. However, if we consider many players we have a higher chance to prove that proposals of players depend on who the partner is for the proposal.

For one pair of compared sets we can calculate the percentage of cases when the fake distance was smaller than the reference one. In this way we can get one number (percentage) for one pair of compared sets. If we have N pairs of sets to compare, we can get N numbers. These percentages can be averaged and then we calculate the probability that such a large (or larger) average percentage can be observed just by chance.

Let us assume that probability that a fake distance will be smaller than the reference one is equal to ν. Then the probability of the given ordered sequence of the results of the comparison can be given by:

$$p(n, \nu) = \nu^n (1 - \nu)^{N-n}, \tag{11.8}$$

where n is the number of comparisons in which the reference distance was larger than the fake one and N is the total number of comparisons. Since we are interested in the probability that in a particular number of comparisons the fake distance will be smaller than the reference one, we need to multiply the above probability by the total number of ordered sequences that contain the same number (n) of the mentioned results.

$$P(n, \nu) = \nu^n (1 - \nu)^{N-n} \frac{N!}{n!(N-n)!}. \tag{11.9}$$

The number of the sequences of the interest are obtained by all possible permutations of the original sequence ($N!$) excluding permutations of the same results of the comparison ($n!(N-n)!$).

The probability ν depends on the value of the reference distance. If we assume that the reference distance is just one of the fake distances (*i.e.*, the two compared sets of decisions were obtained with the same decision maker), then the probability to get such a reference distance that is larger than ν of fake distances is equal to $1 - \nu$. In other words, the ν is distributed uniformly between 0 and 1.

We want to know the probability of n positive results not for a given reference value (and associated with it probability ν) but for the case in which the reference distance is just one of the fake distances. For that we have to integrate over ν.

$$P(n) = \int_0^1 \nu^n (1 - \nu)^{N-n} \frac{N!}{n!(N-n)!} d\nu. \tag{11.10}$$

To integrate the above expression we use the following well-known formulas:

$$\int_0^1 x^n (1-x)^m d\nu = \frac{\Gamma(n+1)\Gamma(m+1)}{\Gamma(n+m+2)} \quad for \quad Re(n) > -1 \wedge Re(m) > -1, \tag{11.11}$$

where $\Gamma(x)$ is the gamma function. Here we can use the fact that for the positive integer arguments $\Gamma(n) = (n-1)!$. Using the above formula we can rewrite equation 11.10 in the following form.

$$P(n) = \frac{n!(N-n)!}{N+1} \frac{N!}{n!(N-n)!} = \frac{1}{N+1}. \tag{11.12}$$

The above result has a simple interpretation. The derivations show that the probability that the fake distance will be n times smaller than the reference distance in N comparisons does not depend on the n. This result is expectable since, according to our assumptions, the reference distance is just one of the fake distances and, therefore, it has equal chances to be smaller or larger than the reference distance. We can approximate the discrete distribution given by formula 11.12 by continuous uniform distribution, if the number of the comparisons (N) is large and we replace the number of positive comparisons (n) by the percentage of the positive cases.

If we have just one pair of sets, we have one reference distance between the sets and a big number of the fake distances. The comparison of the fake distances with the reference one gives the percentage of positive comparisons. If it is very high, it is very likely that the two sets are statistically different. However, for the small difference between the compared pair of sets, the value of the percentage is just slightly more likely to be above 50This problem can be solved if we have a sufficiently larger number of pairs of sets. In this case we can get the average percentage and use it to determine how likely is the given value under condition that the compared sets are statistically indistinguishable.

To perform this procedure we have to calculate the probability distribution function for the average of n_{exp} numbers obtained by the same uniform distribution. This problem can be solved by using the IrwinHall distribution, which is defined as a probability distribution for a random variable defined as the sum of a number of independent random variables, each having a uniform distribution. The Irwin-Hall distribution is given by the following formula:

$$f(x,n) = \frac{1}{2(n_p-1)!}\sum_{k=0}^{n_p}(-1)^k\binom{n_p}{k}(x-k)^{n_p-1}sgn(x-k), \tag{11.13}$$

where n_p is the number of the values which are summed up. Since in our case we need to know the distribution of the average (not the sum) of the numbers we should slightly modify the Irwin-Hall probability distribution function:

$$p(x,n) = \frac{n_p}{2(n_p-1)!}\sum_{k=0}^{n_p}(-1)^k\binom{n_p}{k}(x\cdot n_p-k)^{n_p-1}sgn(x\cdot n_p-k), \tag{11.14}$$

Since we need to know the probability that the average percentage is equal or larger than a given (observed) percentage we need to calculate the cumulative distribution function of the above distribution.

$$P(x,n) = \frac{1}{2}+\frac{1}{2n_p!}\sum_{k=0}^{n_p}(-1)^k\binom{n_p}{k}(x\cdot n_p-k)^{n_p}sgn(x\cdot n_p-k), \tag{11.15}$$

This expression gives the probability that the average value is smaller or equal to the x. Finally, we get the expression percentage of cases in which the average percentage was equal or larger than the given value x:

$$F(p,n_{exp}) = 100.0[1-P(p_{av}/100,n_{exp})] \tag{11.16}$$

11.4 Minimization Procedure for Calculation of Utility Parameters

We have used the measures of inconsistency, defined in chapter 6.2, to calculate the utility parameters of players. Specifically, for every player we run a minimization procedure in the utility space to minimize the given measure of inconsistency. The minimum search starts from a random point in a 3D cube given by the following inequalities:

$$\omega \in (-1, 1) \wedge f \in (-1, 1) \wedge g \in (-1, 1)\,. \tag{11.17}$$

On every step of the minimization procedure we try to shift over every three dimension (utility parameter) in both directions by a current step. So, in total we calculate the measures of inconsistencies in six neighboring points. We shift to the point in the utility space that gives the smallest value of the inconsistency level. If none of the neighboring points gives a smaller value, we stay in the current point and reduce the step by the factor 1.1. The initial step of the minimization procedure is 0.1. We stop the search if the step is smaller than 10^{-4} or if the number of iterations exceeds 10^5. This procedure ends up in one of the local minimums. To solve the problem of the local minimum we repeat the procedure many times and choose the point that gives the smallest value of the inconsistency level. If there are several points corresponding to the smallest value of the inconsistency level, we choose the point that minimizes the RMSD from all other points from the set. Roughly speaking we choose the point from the center of the region that provides the smallest value of the minimized criterion.

12. PUBLICATIONS

Journal papers in preparation:

- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M., **Estimation of social preferences of decision makers with cognitive horizon**, *in preparation.*
- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M., **Quantitative measures of cooperative behavior in games**, *in preparation.*

Submitted journal papers:

- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M., **Utility function describing social preferences in multiplayer games**, *IEEE Transactions on Computational Intelligence and AI in Games, under review*
- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M., **Use of genetic programming for explanation of time dependent facial expressions in terms of hidden emotional event**, *IEEE Transactions on Evolutionary Computation, under review*
- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M., **Measuring interpersonal cooperation through tailored games involving social dilemmas**, *Entertainment Computing (official IFIP journal), under review*

Published papers:

- Gorbunov, R., Barakova, E., Rauterberg, G.W.M. **Design of social agents**, *Neurocomputing, in press, accepted manuscript*; http://dx.doi.org/10.1016/j.neucom.2012.06.046
- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M. **Monitoring facial expressions during the Mars-500 isolation experiment**, *The 8th International Conference on Methods and Techniques in Behavioral Research, 2012*
- Gorbunov, R., Barakova E., Rauterberg, G.W.M. **Interpretation of time dependent facial expressions in terms of emotional stimuli**, *International Conference on Evolutionary Computation Theory and Applications (ECTA), 2012*

- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M. **Adaptive properties and memory of a system of interactive agents: A game theoretic approach**, *The Fourth International Conference on Adaptive and Self-Adaptive Systems and Applications, 2012*

- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M. **Generalized utility describing cooperation and fairness**, *The 8th Spain-Italy-Netherlands Meeting on Game Theory, 2012*

- Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M. **Monitoring interpersonal relationships through games with social dilemma**, *Proceedings of International Conference on Evolutionary Computation Theory and Applications (ECTA).* pp. 5-12, Paris, France, October 2011. [Best Paper Award]

- Gorbunov, R., Barakova, E., Rauterberg, G.W.M. **Design of social agents**, *Lecture Notes in Computer Science*, Volume 6686, pp. 192-201, 2011

- Voynarovskaya, N., Gorbunov, R., Barakova, E., Ahn, R., Rauterberg, G.W.M. **Nonverbal behavior observation: Collaborative gaming method for prediction of conflicts during long-term missions**, in H.S. Yang et al. (Eds.): *International Conference on Entertainment Computing (ICEC)*, LNCS 6243, pp. 103-114, 2010.

- Voynarovskaya, N., Gorbunov, R., Barakova, E., Rauterberg, G.W.M. **Automatic mental health assistant: Monitoring and measuring nonverbal behavior of the crew during long-term missions**, *Proceedings of 7th International Conference on Methods and Techniques in Behavioral Research, Eindhoven, the Netherlands, ACM, 2010*

13. MONITORING EMOTIONS AND COOPERATIVE BEHAVIOR: SUMMARY

Cooperation among people in teams that are bound to perform a common goal is one of the main factors determining success of these teams. Cooperation becomes even more important for small teams performing long-term missions in isolation. Examples of such missions include missions performed on the international space stations, polar research stations, submarines, oil platforms and meteorological stations. Such missions are usually performed in extreme physical and psychological conditions that have a strong negative effect on emotional states of the crew members and interpersonal relationships between them. This work presents a set of methods for an automatic measuring of cooperative behavior and emotional states in goal-oriented teams performing long-term missions in isolation. The proposed methods were tested on and applied to data from the Mars-500 isolation experiment. The methods are based on analysis of two kinds of data: behavior in a cooperative computer game and video records of facial expressions.

Chapter 2 introduces the Colored Trails (CT) game that is used as a research test-bed for investigating decision-making in groups comprising people, computer agents, and a mix of these two. Chapter 2 also proposes to use the CT game with specially designed payoff spaces that make it easier to tie decisions of the players in the game with the social preferences of the players.

Chapter 3 introduces a numerical parameter describing the propositions made in the CT game in a way that is relevant to cooperative and fair behavior of players. This parameter has been used to demonstrate that different players have different social preferences.

To describe cooperative behavior of players in the proposal phase of the game two ratios were introduced in Chapter 4. The first ratio, called level of cooperation, is used to describe preferences of each player over cooperation and fairness. The second ratio, called symmetry of cooperation, describes difference between sacrificing and exploiting behavior of players. The introduced ratios provide a quantitative way to describe cooperative behavior of players in the game. Chapter 4 demonstrates that different players behave differently in terms of the introduced ratios. Moreover, the behavior of a player can depend on who his/her opponent is in the game. It indicates that cooperative games can be used to capture some cooperative aspects of interpersonal relationships between different players.

Chapter 5 proposes a utility function that describes cooperation and different kinds of fairness. To derive this utility function, Chapter 5 starts from

building a link between the social-welfare and inequity-aversion utility functions that are well established in literature. Moreover, the way in which these functions are generalized to the case of more-than-two subjects is considered and an alternative generalization procedure is proposed. Finally, the utility function is extended by adding a term that models an additional type of fairness. For the case of two players, the introduced utility function contains three parameters describing the players' social preferences. The utility-based approach can be considered as a more general than the approach based on the use of cooperation ratios because the two cooperation ratios can be obtained from the values of the three utility parameters but the opposite is not true.

Chapter 6 considers influence of the combinatorial complexity of the game on the decisions of the players to develop a model that can explain non optimal decisions of the players in the game. Three parameters that determine combinatorial complexity of the decisions in the game were identified and their influence on the decisions of each player has been demonstrated. To find correct values of the utility parameters, describing social preferences of a player, it is necessary to take into account the fact that the ability of players to find options in the game is limited by the combinatorial complexity of the game. To do that, different measures of inconsistency between a given set of utility parameters and a given set of decisions were proposed. It is demonstrated that a correct choice of a measure of inconsistency is very important for the proper estimation of the utility parameters. Moreover, a model-based approach to the construction of the inconsistency measures was proposed and it was demonstrated that this approach provides a better way to estimate the utility parameters of the players.

Chapter 7 presents a method for description of the social preferences of the players revealed in the response phase by a network of player's preferences over different types of proposals. Different ways to quantify these preferences were proposed. A link between the methods, developed for the proposal and response phases of the game has been made and, in this way, it has been demonstrated that the parameters calculated for the different phases and describing social preferences of the players are in a statistically significant agreement.

Finally, Chapters 8 and 9 are devoted to analysis of video records of facial expressions taken during the experiment. For the analysis of the facial expressions different statistical properties were introduced, their classification was given and their meaning was described. By considering these properties two interesting results were found. First, there is a statistically significant correlation between the emotional states of the crew for the neighboring experiments (separated by two weeks). Second, different types of the relations between the facial expressions of different users were found. A possibility to use these relations as quantitative measures of emotional bonding of different types and strengths was discussed. In addition to the use of the statistical properties a mathematical model that could help to interpret time-dependent facial expressions in terms of events inducing emotions was developed. With the proposed method the locations of these events in time as well as the type and value of the impact that these events have on emotional states can be found.

In summary, a methodological toolbox for an automatic monitoring of the psychosocial atmosphere in small groups performing long-term missions in isolation is proposed. The possibility to use computer games to monitor interaction between crew members and, in this way, access some aspects of their interpersonal relations was studied. Special attention has been paid to cooperative aspects of interpersonal relations. To monitor emotional states of the crew members commercial FaceReader software has been used. The works focuses on the method of analysis of facial expressions, which are relevant to the monitoring of interpersonal relations and long-term effects of isolation.

This work can be considered as a first step in the development of systems for an automatic monitoring of psychosocial atmosphere in goal-oriented teams. A lot of additional research and testing has to be done before a comprehensive system of this kind can be created. Further progress in this area would involve the following: First, the games used for a monitoring of interactions between the crew members have to be made gradually richer in terms of the decision making situations to capture different aspects of interpersonal relations. Any extension of the games has to be supported by a development of theories for analysis and interpretation of the playing behavior in the extended settings. Second, the combinatorial complexity of the game has to be decreased to decrease the time needed for making decisions and, in this way, increase the number of decisions (data for analysis) per game. Moreover, reduction of the combinatorial complexity can help to separate effects of social preferences from the effects of complexity.

For a more comprehensive monitoring of emotional states, measurements of voice intonations look very promising since humans are shown to express their emotions through facial expression and voice intonation. Moreover, usually people express their emotions through voice intonation during their communication with each other. This aspect can be very interesting in the context of monitoring interpersonal relations.

Finally, a progress in the development of tools for an automatic facial expression recognition and voice intonation interpretation can be accomplished by the development of methods for analysis of the data generated by these tools. In other words, we need models that can bind the observed (and classified) facial expressions and voice intonations with underlying psychological processes in a deeper way.

14. CURRICULUM VITAE

Roman D. Gorbunov was born on 07-09-1978 in Dniprodzerzhynsk, Ukraine. He studied theoretical physics at Dnipropetrovsk National University in Dnipropetrovsk, Ukraine. In 2000 he received the M.S. degree in Theoretical Physics (diploma with honors). From 2003 he started a PhD project in Quantum Chemistry at Goethe University in Frankfurt am Main, Germany and received PhD title in 2007. From 2007 to 2009 he worked as Postdoctoral Research Associate at Biophysics and Physiology Department at Albert Einstein College of Medicine, Yeshiva University in New-York, USA. From 2010 he started a PhD project at Eindhoven University of Technology in Eindhoven, Netherlands of which the results are presented in this dissertation. Since 2013 he is employed as a data scientist at Blue Yonder in Karlsruhe, Germany.

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