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GAMES THEORY INVOLVEMENT IN THE SOCIAL ROBOTS' FACIAL EXPRESSIONS

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This paper presents a method based on games theory and coordination graphs with the aim of improving the social robot facial expressions to perform human-like motions. It is an alternative to the neural networks or fuzzy logic methodologies. The difficulty is raised by the increased number of servomotors which should be controlled, and the translation of the motion of more than 40 face muscles to get the proper facial expression. There are evaluated four emotions using coordination graphs. The games are described by matrices of three or five players, and the dominance and equilibrium states are evaluated using Gambit software.

Keywords: games theory, coordination graphs, Androids, facial expressions, social robots

1. Introduction

The human face is the key factor in the relational communication between people, and it is one of the sensitive regions of the human body. The face conveys emotions interpreted by our peers as pleasure or disgust, real smile or fake, sadness, fear, or anger. All these emotions became of a real interest for researchers from different areas, from psychology to computer science, electrical engineering, and robotics to transpose it to the synthetic organisms - the Androids, a Science Fiction subject till few years ago. Ekman established a coding system for facial expressions (FACS) in terms of anatomic muscle movements, called action units and coded the action unit's intensity in 5 discrete levels depending on the face changeset, [1]. Based on the 'dictionary' of Ekman more researchers have been developed emotions for Androids considering typical facial expressions: surprise, fear, disgust, anger, happiness, sadness, [2]-[4], which are universal and associated with the same facial expressions over different cultures, [24].

In the last years Androids met an ascending development and evolution starting from 13 degrees of freedom (DOFs) used for the face muscles movements and arriving today up to 35 DOFs. The importance of DOFs is given in the coordination graphs and involvement in the muscle's motions. A summary about

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Androids can be found in [11], remembering about the first Android developer Cynthia Breazeal and her robot called Kismet, which was able to display an extensive assortment of facial expressions [5], or David Hanson who came with the most advanced Androids thanks to the Frubber skin material which allow the robot to mimic the human facial expressions extremely realistic (Einstein, Eve, Sofia, Phillip K. Dick, Zeno) [8]-[11]. Also, we should mention about Hiroshi Kobayashi and his SAYA robot [12] or Hiroshi Ishiguro, a remarkable developer of Androids. Today, we have the AMECA robot developed by the Engineered Arts, a UK leading designer and manufacturer of humanoid robots [32].

Other robots that can be mentioned here are: EveR1, DER2 or ROMAN. EveR1 uses a hydraulic system to mimic the human emotions and motions of the head, arms and upper body movement and lips synchronization through 35 DOFs [2], [13]. DER2 is not only an Android, but also an Actroid who changes expressions, moves its hands, feet and twist its body by using 13 DOFs for the face and highly sensitive tactile sensors mounted under the skin [6]. ROMAN head is build using other mechanical concepts, 8 metal plates are moved via wires, and the action units are realized according to 10 servomotors who pull and push the wires. Its neck movement is obtained with 4 DOFs.

Previous works on the Androids development included neural networks, fuzzy logic, genetic algorithms, or neuro-fuzzy systems. Neural networks shown a good fitting for learning Androids and control systems with a high number of DOFs [11]. A growing neural network is used based on the process consolidation determining the network structure adaptively. Because between levels of learning intervenes mixtures of old and new learned knowledge, the growing neural method acts as an adaptive memory assigning regularly new data learned. [11] proposed an automated methodology, without using markers on the PKD face and with a high degree of generality. The method is based on neural networks employing a genetic algorithm which helps to search the servo-motors space, but also to generate a large set of facial expressions. The method can be applied for any Android showing an excellent learning and accurate facial expression. The classification of the intelligent systems is obtained using fuzzy logic and case-based reasoning of [19], blended to provide a solution for a hybrid system. The facial expression recognition is obtained from an input image, then is used a case base populated with fuzzy rules for identifying each expression, [19]. [20] proposes to use Madami-type fuzzy rules to classify and improve the performance of a hybrid system and uses Genetic learning processes to optimize and improve the accuracy and the robustness of the system. The objective of alternating Fuzzy rules with Genetic Algorithms is to reduce the time for training and classify accurately the problems which show a fragile distinction between two classes. Even Fuzzy Logic is widely used in academic and industrial applications, the method does not cover the effortless, so neuro fuzzy inference expert systems are developed based of Takagi-Sugeno-type fuzzy inference systems, [21].

Many works and efforts were assigned to emotional features extraction which is a tremendous step in facial expression recognition. [15] improves the facial expressions recognition using a Gabor filter, so that facial movements features are extracted as static images based on distance features, 'salient' patch-based Gabor features, and then are performed patch matching operations. To predict the human facial expressions, [16] developed a method based on strategic decisions, a new version of centipede game. There are recorded videos form different subjects playing centipede games, and the resulted data vector is used as an input to classify the predicted decisions. This method is the first one who is trying to predict people strategic decisions.

This paper is organized as follows: in section 2 is described the games theory method, including an overview about players, actions and set of actions describing the games theory, global payoff functions and expressions for the exchange of messages between neighboring players. In section 3 is given a brief presentation of the Android. Section 4 will present the adopted method for the Android (description of action units for eyebrows, eye lids, mouth, and jaw), matrix for games between 3 players or 5 five players and their corresponding global payoff functions. Finally, in section 5 and section 6 respectively, there are presented the results and discussions about future works.

2. Games theory and Coordination graphs

A. Games Theory and Components

By definition, the basic components of a strategic game are: a set of players $P = \{1,2,...,n\}$ also called decision makers, a set of actions for each player $A_i = \{a_1, a_2,..., a_m\}$ and payoff functions for each player, $R_i = \{R_1, R_2,..., R_p\}$, [26]. The game environment is translated by a payoff matrix which is a kind of graphical representation of coordination games between two or more players and the quantifiers of the matrix can change according to the dynamics of the game, [25], [26].

For games with multiple players that react dynamically between them it can be introduced the concept of dynamic systems games. These types of games are characterized by a natural law (the change of information between players is based on natural law), each player is designed with its own decision-making mechanism and the changing produced in the system is affected by the other decision's players, [26]. A decision making is a function $f_{ij}(a_i, a_j)$, where the f_{ij} gives player a_i all possible activities, and the same function f_{ij} can change its rules through evolution or learning process, meaning that this function provides the player's personality, [26]. From a_i is sent the decision to a_j that continue the game following the best response. If into a strategic game are two best responses, then the Nash equilibrium concept will be applied. It will be established a joint action $a^* \in A$, (A is the joint Action) respecting the property that every player holds $R_i(a^*, a^*_{-i}) \geq R_i(a_i, a^*_{-i})$ for all actions $a_i \in A$, and a_{-i} represents the joint action for all players excepting player *i*. In this case the players keep the same strategy profile, [29].

Another concept that should be taken into account is the Pareto optimality, which is translating that an $a^* \in A$ action is optimal if there is no other joint action *a* for which $R_j(a) \geq R_i(a^*)$ for every players and $R_j(a) \geq R_j(a^*)$ for at least one player *j*. In every game, a Pareto optimal solution is always a Nash equilibrium, [26].

B. Coordination Graphs

From the dynamic game results, a single or multiple graphs which are coordinated with methods like variable elimination or different algorithms, [27]. A coordination graph G=(V,E) is designed with V vertexes representing the number of players and E edges, representing the messages between players respectively. The global payoff function of a graph G can be represented as follows:

$$u(a) = \sum_{(i,j)\in E} f_{ij}(a_i, a_j) + \sum_{i\in V} f_i(a_i) \tag{1}$$

where f_i is the local payoff function for each player *i* that serves the action a_i, and f_{ij} is the local payoff function mapping two actions a_i and a_j to a real number $f_{ij}(a_i, a_j)$. f_i acts individually and f_{ij} has a coordinated action. For equation (1) we are looking to optimize its value and find a^* that maximizes the equation (1).

The coordination problem can be interpreted as a problem of selecting a single Pareto optimal Nash equilibrium, using learning alternatives when the game is played repeatedly, including communication when the player informs other *p* neighbors by restricting the choice of the other players to a simplified coordination graph or social convention when for each player are conceived constraints, [26]. In robotics applications the coordination graphs are applied only for robots closed to each other, [26].

The messages μ_{ij} between players are expressed by equation (2):

$$\mu_{ij}(a_j) = \max\{u(a) + \sum_{k\in\Gamma(i)\setminus j} \mu_{ki}(a_i)\} + c_{ij} \tag{2}$$

where *u(a)* represents the global payoff function of the graph G, $\Gamma(i)\setminus j$ are all neighbors of player *i* except *j*, and c_{ij} is a normalized vector between players *i* and *j* computed by equation (3).

$$c_{ij} = \frac{1}{|A_k|}\sum_{K} \mu_{ik}(a_k) \tag{3}$$

The message μ_{ij} is exchanged between players until they reach the desired action. In the case of the Android described in section 3, the messages are exchanged until is obtained a desired emotion.

C. The Max Plus Algorithm

The Max-Plus Algorithm was successfully applied for soccer games with multiple players [26]. The algorithm is an analog version of the belief propagation or the sum-product algorithm in Bayesian networks and calculates the maximum a posteriori configuration in an undirected model, [30]. The algorithm is applied for a global payoff function expressed in (1) for a graph G with V vertexes and E edges respectively. Each player *i* send a message μ_{ij} to its neighbor's *j*, and an action a_j of a player *j* will be mapped to a real number expressed by equation (2). The value of μ_{ij} represents an approximation of the maximum payoff that a player *i* can accomplish for every action of player *j*, and is calculated by maximizing the global playoff function *u(a)* which is the sum between the payoff functions of f_i and f_{ij} respectively, and all incoming messages to player *i* except that from player *j*. The sequence is repeated until μ_{ij} converges and takes the value $g_i(a_i)$ and is proved by equation (4) that $g_i(a_i) = \max\{a' | a_i^{'} = a_i\} u(a')$ holds, [26].

$$g_i(a_i) = f_i(a_i) + \sum_{j\in\Gamma(i)} \mu_{ji}(a_i)\} \tag{4}$$

After this step, player *i* chose the optimal action expressed by $a^* = \arg\max_{a_i} g_i(a_i)$. If every player will have a single maximizing action, the entire optimal joint action $a^* = \arg\max_{a_i} u(a)$ is unique and its elements are equal to a_i^*, [30]. The Max-Plus Algorithm can be implemented in centralized coordinated graphs, but also in distributed coordination graphs, [26].

3. Description of an Android

In this section we introduce a description of an Android with particularities and constraints that should be considered for section 2 and section 4 respectively. Additional descriptions can be found in [11], where contributions and works of the team are presented.

We distinguish at least three generations of Androids. For the first generation we can include Kismet or ROMAN robots with the head about 1.5 times bigger than the human head, but not enough ideal because of the deformations in a confined area of soft material facial skin, [4]. The second generation succeeds in realization of the human head size but had not enough power available to implement the real time tasks, [4] and was developed using the method based on shaped memory alloy actuator driven by electricity, [28]. The Android from [11], [12], and [32] is part of the third generation of Androids with particularities and innovations from the point of view including novel facial materials, underlying expression mechanisms, new approaches to anesthetic unification of these into an appealing humanlike robot, [11], [24]. All third-generation robots present increased number of DOFs placed to pulls the skin along vectors corresponding to the human facial muscle actions (eg. zygomatic, frown, forehead, smile, procerus, orbicularis oculi, etc.).

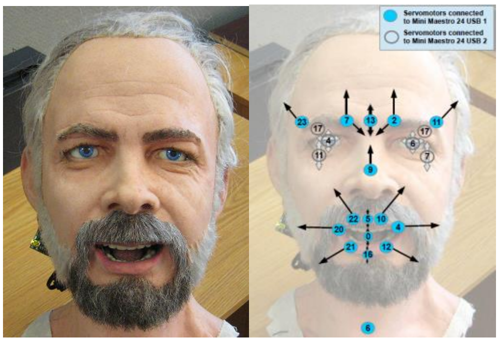


Fig. 1. Android Head and Position of Servo Motors , [11].

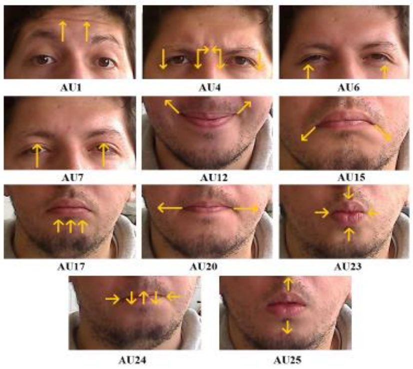


Fig. 2. Action Units, [3] .

An example of servomotors/DOFs arrangement into a robotic head is given in Fig. 1, where can be identified the position of some servomotors that realize movements of the face and the direction to which can act. The total number of DOFs for this robot is about 24 servomotors and the robot can control the expressions of the face involving the eyebrows, eyelids, lids and lips, and the rest of them control the neck obtaining the yaw, pitch and roll movements. In some cases, one motor will replicate the action of two opposing muscles since muscles only contract, while the motors are reversible. Electrical and mechanical design, commercial software and other additional particularities are given in [11].

4. Modeling facial expressions and Games theory for the Android

A. Action Units selected for the Android emotions

To apply games theory for the Android described in [11], the robot face is decomposed in action units as shown in [3], (see Fig. 2) and adapted as given in Figure 3 (a-d). A reunion of several action units will map four different emotions of happiness, sadness, fear, or anger as shown in Table 1, including 14 action units (AU0, AU1, ..., AU24) and 24 servomotors of the Android. For example, AU0 involves servo number 0, for AU1 servos 2, 7 and 13, AU4 servos 11 and 23, AU6 servos 11 and 7, AU7 servo 17, AU12 servos 4 and 20, AU15 servos 12 and 21, AU25 servos 5, 10 and 22. It is important to note that the action units of the Android are following the action units' numbers shown in the four images given in Figure 3. Please note that scientists identified 27 emotions that the human face can express [33], however in this work for simplification we selected only four emotions which are the most common categories evaluated in primary studies.

The action units take in their componence the movements of the eyebrows, eyelids, eyes, mouth, and jaw. Once implemented this method, the games theory can be extended for the neck-eyes coordination and for multiple emotions that the face can express.

Table 1

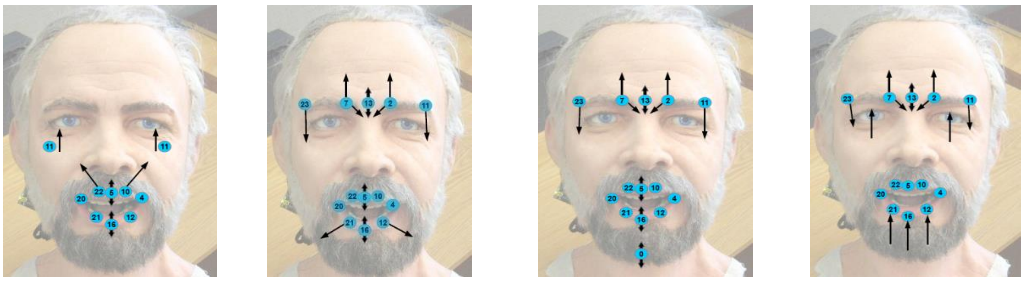
Movements for the Hanson Android's components associated with emotion

	Actions	**Face components**
Neutral	-	-
Happy	AU6-AU12- AU25	Eyebrows -Eyelids-Eyes-Mouth
Sad	AU1-AU4-AU15-AU17	Eyebrows -Eyelids -Eyes
Fear	AU1-AU4-AU20-AU25-AU0	Eyebrows -Eyelids -Mouth
Anger	AU4-AU7-AU17-AU23-AU24	Eyebrows -Eyelids

The all-possible actions that players can have, are the following: A1 move up/down the eyebrows, A2 move up/down/left/right the eyes, A3 open/close the eyelids, A4 move up/down the nose, A5 open/close the mouth, A6 move up/down the jaw. The set of actions for each player can be {move up, stay, and move down} or {move left, stay, move right}. The values attributed for each action are -1 for move down/move left, 0 for stay and 1 for move up/move right. Recognizing these values in the Max-Plus algorithm an implemented function will be called to execute the task for every servomotor involved in the game at his turn of action.

B. Design of Matrix for Games with 3 players

The coordination game is described by a graphical representation as shown in Table 2, Table 3 and Table 4 respectively, where there are discussed all possible actions that can be taken by each player involved into a game; in our case the players are the servomotors of the Android. A player has the role of one single servomotor. For example, the motion of the left and right brow involves five servomotors, which means that the brows motion is achieved by five players from the game. These 5 players constitute a team (Team 1). And if we consider a second team (Team 2) who acts on the upper lip, and a third team (Team 3) who acts on the lower lip, these three teams need to synchronize between them to achieve the right emotion, but also need to synchronize as well with the other teams involved in the facial expressions (eg. eyes motions, forehead motion, nose, jaw motions).



(a) Happy Face (b) Sad Face (c) Fear Face (d) Anger Face

Fig. 3. Android emotions decomposed following the action units, based on [11]

The game can have one or more players and we need to design matrices with n payoff functions for the n players. In the three tables it is presented a game between 3 players characterized by 3 different actions for every servomotor/player that can execute. This is a simultaneous three-player game, and this is the reason why we can see not only one matrix but three matrices. The game between two players will have only one matrix (see Table 5). The method will be applied for different action units, for example for the coordinated graph designed for the eyebrows or mouth movements.

Table 2

Coordination game for 3 players, the first player executes a certain movement (Up)

13 (Up)	11 (Up)	11(Stay)	11 (Down)
2 (Up)	(1, 1, 1)	(1, 1, 0)	(0, 1, -1)
2 (Stay)	(1, 0, 1)	(1, 0, 0)	(1, 0,- 1)
2 (Down)	(1,-1, 1)	(1,-1, 0)	(1, -1,-1)

Table 3

Coordination game for 3 players,the first player execute a certain movement (Stay)

13 (Stay)	11 (Up)	11(Stay)	11 (Down)
2 (Up)	(-1, 1, 1)	(-1, 0, 1)	(-1, 1, -1)
2 (Stay)	(-1, 0, 1)	(-1, 0, 0)	(-1, 0,- 1)
2 (Down)	(-1,-1, 1)	(-1,0, -1)	(-1, -1,-1)

Table 4

Coordination game for 3 players, the first player execute a certain movement (Down)

13 (Down)	11 (Up)	11 (Stay)	11 (Down)
2 (Up)	(1, 1, 1)	(1, 1, 0)	(0, 1, -1)
2 (Stay)	(1, 0, 1)	(1, 0, 0)	(1, 0,- 1)
2 (Down)	(1,-1, 1)	(1,-1, 0)	(1, -1,-1)

Table 5

Coordination game for 2 players, with 3 actions for each player

2 or 11	11 (Up)	11(Stay)	11 (Down)
2 (Up)	(1, 1)	(1, 0)	(1, -1)
2 (Stay)	(1, 0)	(0, 0)	(0,- 1)
2 (Down)	(1,-1)	(-1,0)	(-1,-1)

The individual team could include: one player (eg. the motion of the nose), three players (eg. the motion of one single brow or the motion of the eye), five players (the motion of both brows, the motion of the upper or lower lips). However, one player can participate in two teams (player 4 and player 20 for the mouth motion).

The odd number of players comes from the fact of the servomotor's placement in the robot skull and because of mechanical, geometrical or symmetry constraints.

An even number of players could be considered for the control of the mouth (8 players). However, for simplification should be considered two teams, each team controlled by five players, and two of then serve both teams (servomotor 4 and servomotor 20 respectively). To achieve the right emotion, all teams (implicitly all players) should collaborate with high accuracy.

The dominance and equilibrium states will be studied using Gambit, a software design with tools for Games Theory, [31]. The software provides a tool to build the games between multiple players, analyze their decision strategy and explore the game models.

C. Global Payoff function

In this section it will be developed a global payoff function for a coordination graph built for the eyebrow's movement. In this graph five servomotors (player) should be coordinated (servomotor 13 for the brow – center position, servomotor 2 for the brow – left direction, servomotor 7 for the brow – right direction, servomotor 11 for the forehead – left direction, servomotor 23 for the forehead – right position). In figure 4 is shown the coordination graph for five players being indicated the servos numbers and the exchange of messages between players.

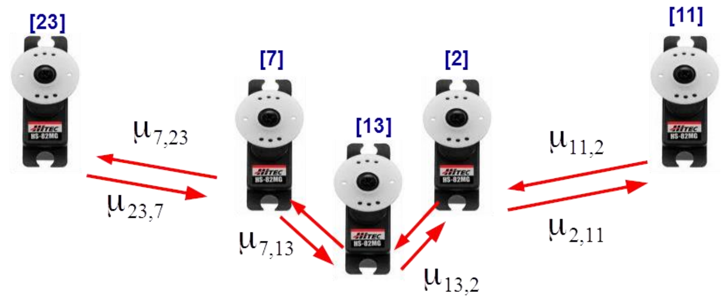


Fig. 4. Coordination graph for five players (eyenbrows movement)

The global payoff function is given by equation 5 and the exchenge messages between players are calculated following expression (2), as in equation (6) and (7). In the same manner will calculated the other messages. The vector *c* will be calculated following expression (3).

$$u(a) = f_{13}(a_{13}) + f_2(a_2) + f_7(a_7) + f_{23}(a_{23}) + f_{11}(a_{11}) + f_{13,2}(a_{13}, a_2) + f_{13,7}(a_{13}, a_7) + \\ + f_{2,11}(a_2, a_{11}) + f_{7,23}(a_7, a_{23}) \tag{5}$$

$$\mu_{13,2}(a_2) = \max\{ f_{13}(a_{13}) + f_{13,2}(a_{13}, a_2) + \sum_{k \in \Gamma(13)\backslash 2} \mu_{k,13}(a_{13})\} + c_{13,2} \tag{6}$$

$$\mu_{2,13}(a_{13}) = \max\{ f_2(a_2) + f_{2,13}(a_2, a_{13}) + \sum_{k \in \Gamma(2)\backslash 13} \mu_{k,2}(a_2)\} + c_{2,13} \tag{7}$$

The values of the local payoff function of each player and the payoff functions between players will be selected from the matrix containing the payoff function values. Taking a careful look at the number of servomotors included in the mouth movements, there are in number of 10. The same principle applied to the eyebrows can be implemented for the upper and lower lips of the mouth. The coordination graph will be integrated in the real time software developed for controlling the Android. The Max Plus algorithm will converge the messages until is reached the position of each servomotor, for example provided by a Kinect position sensor. The position values transmitted by the position sensor will describe a certain emotion of the Android.

5. Results

In Fig. 5 and Fig. 6 there are shown the corresponding graphs for the game with 3 and 5 players respectively obtained using Gambit software, and which provides an environment to analyze the equilibrium and the dominance of every strategic game with multiple players. Additional explanations about Gambit can be found in [31]. In both figures can be seen the equilibrium between players related to their actions. Each color from the graph represents a player, so that the motion of the player and its payoffs can be followed.

In Fig. 5, player 1 is recognized by the red color, player 2 by blue color, and finally player 3 by the green color. Similarly, we identify in Fig. 6 the five players. The software allows us to compute the equilibria with accuracy, and to construct numerical approximations close to the equilibrium points. The software will be used for further work, studying the different games between players. For the Max-Plus Algorithm implementation will be used data provided by Kinect, the position sensor, and minimal, neutral, and maximal values for the servomotors position.

6. Conclusions and Future works

The paper presents a history of the evolution of the development of the problem of facial expressions of humanoid robots/Androids, unifies their evaluation concepts by using graph theory, respectively game theory. The performance evaluation approach is based on both empirical methods and specialized techniques from simple to complex and vice versa. We have proposed a method based on games theory which is an innovative idea for Androids designed with facial expressions which can be of a real benefit for this kind of applications, and not only for fighting drones' swarms for example. Researchers put their efforts to involve game theory in the artificial intelligence ([34], [35] and not only), in various applications of robotics (flying robots, humanoid robots, Androids, UAVs), and to identify further directions of improving the nowadays technology. Games theory remain an open research path for artificial intelligence, [34]. The Android face is segmented into several action units, then coordination graphs are proposed to obtain facial movements and integrate all servomotors of the Android in the entire game. As mush servomotors are involved in the possible coordination graphs, as much the facial expressions are close to the human-like motions. The facial muscles are well mimicked if the face has as much more degrees of freedom. The method based on games theory is an innovative idea which was implemented only on cooperative games, such as soccer games.

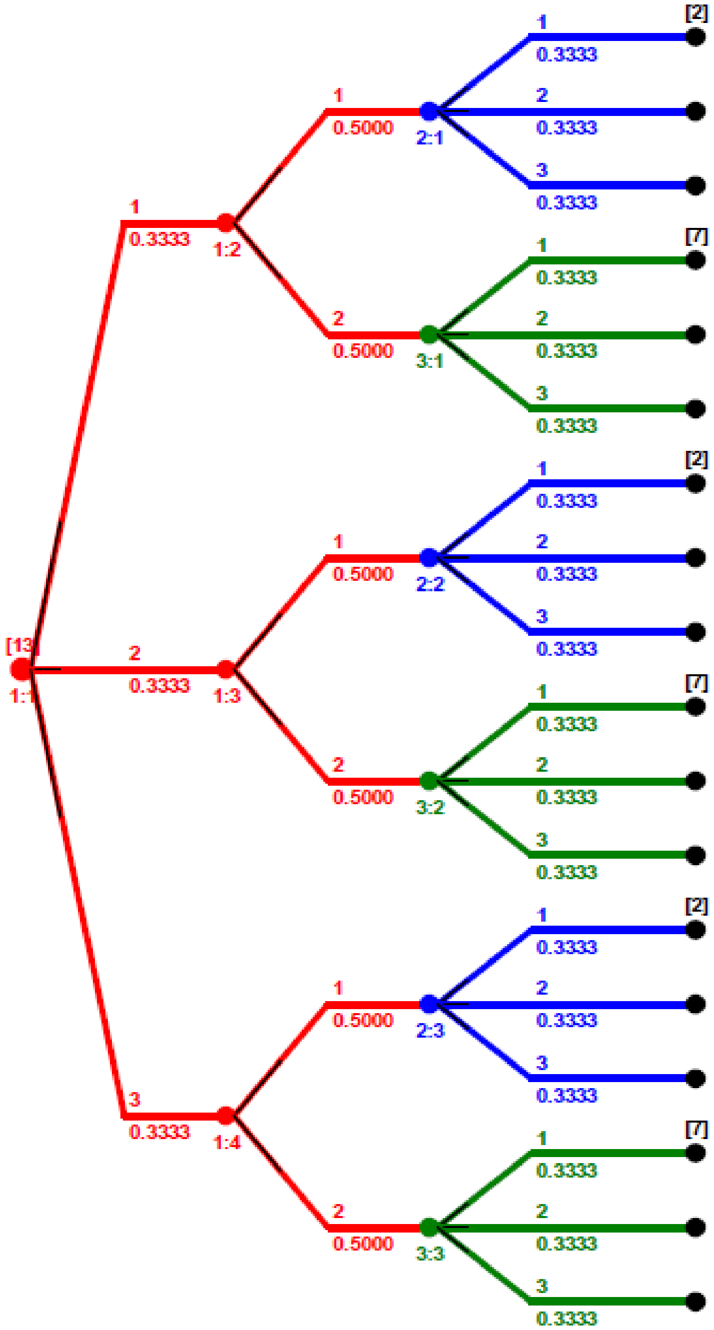


Fig. 5. Equilibrium and Dominance for Games with 3 Players

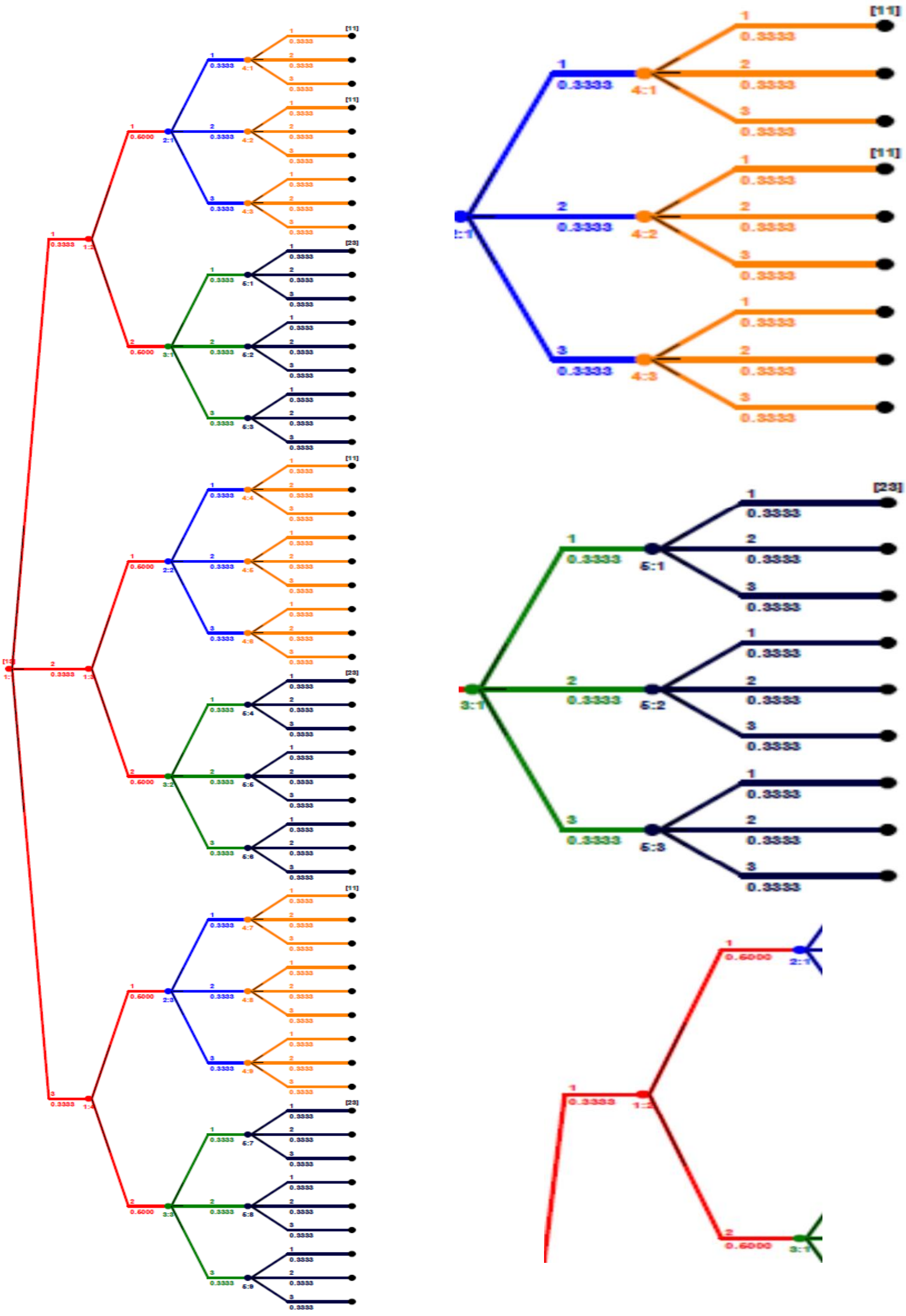


Fig 6. Equilibrium and Dominance for a Game with 5 Players

In this case, the problem is more complex because the servomotors are interconnected and should converge to different but complex expressions (it is not only a mechanical movement that servomotors should execute, it should be obtained a smoothness motion, not dangerous as in surgical robotics but to obtain a human-like face movement). Future work will include the Max-Plus Algorithm implementation for four basic facial expressions (emotions), then will be extended to a various range of facial expressions.

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