

Social Facilitation in a Game-Like Human-Robot Interaction using Synthesized Emotions and Episodic Memory

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Abstract. Companion robots will be more and more part of our daily lives in the next years, and having long-term interactions can have both positive and negative effects on their users. This paper presents an experiment that is focusing on social facilitation. Our scenario is a memory game with the Nao robot and is combining an emotional system based on the OCC Model, and an episodic memory mechanism. Our first preliminary results show evidence that support the theory and present a first step towards an adaptive lifelong learning system.

1 Introduction

Social facilitation effect is a widely studied [7][12] psychology paradigm introduced by [16] that states that individuals get a better performance on easy tasks if they are in presence of others, but their performance is worst in complex tasks. With robots being more and more around people, situations where social facilitation has an effect can appear more frequently. This can have positive or negative influence on the social interaction and the robot needs to be capable of adapting to the user so as to improve the interaction and the user’s task performance.

Very little work in social robotics [15] [10] or virtual characters [9] has focused on Social Facilitation. The authors in [10] presented a study that compared the task performance of 106 participants on easy and complex cognitive and motor tasks across three presence groups (alone, human presence, and robot presence). They found evidence that confirms the theory of Social Facilitation, but they focused on the mere presence of the robot. This paper presents an experiment where the social facilitation effect in Human-Robot Interaction is investigated. The scenario involves a memory card game in which the robot is the opponent of the human player, and it can take two roles: it can encourage or judge the human-user, depending on the game mode.

We also introduce a high-level framework, which integrates an emotional model and an episodic memory, which has the potential to adapt to the user’s preferences based on the robot’s emotions generated by the interactions with the users. The emotional model is a partial implementation of the Orthony Claire

Collins Model(OCC Model) [8] having 6 emotions: love, hate, pride, shame, admiration, and reproach. These emotions are classified in two categories: *Aspect of Objects* and *Actions of Agents*. This last category is of particular importance for the Social Facilitation experiment because both the psychological theory and the OCC Model rely on the performance of the actions of the agents. The OCC Model has been widely implemented in Human-Machine Interaction for virtual animated characters [2] and robotics. The authors in [5] present the development of a robot equipped with the OCC model for their emotion engine, but not in an interaction scenario.

Furthermore, we are using an episodic memory (EM-ART - an episodic memory (EM) using Adaptive Resonance Theory (ART) neural networks [3]), presented in [14] [6]. The EM-ART records sequences of events as episodes. Here, it is used to store information about the games, by recording the sequence of cards obtained by each player.

To the best of our knowledge, there are no works in the literature that fully combine the emotion and the memory system in an interaction for testing social facilitation. This work presents a first step in that direction, using EM-ART as long-term memory to provide useful information to the emotion system based on the OCC Model, and the output of this is used to modulate the intensity of different expressive behaviors.

This paper is organized as follows: Section 2 describes the scenario used and the set up of the methods applied; Section 3 explains the high level framework proposed in this work; Section 4 shows the results obtained regarding the Social Facilitation experiment and the perception of the emotional expressions; and finally, Section 5 concludes the paper.

2 Experimental Design Setup

2.1 Hypothesis

The hypothesis of this work are inspired by the Social Facilitation effect and are formulated as follows:

Hypothesis A: The user’s performance in an easy task while being encouraged by a robot, will be better than while performing the same task alone.

Hypothesis B: The user’s performance in a difficult task while being judged by a robot, will be worst than while performing the same task alone.

2.2 Game Scenario Description

In order to test and validate our system we designed the "Find the Pair" board game. The "Find the Pair" board game is played with a set of cards containing pairs of matching images. The cards are put face down on a grid with letters marking columns from A to D and numbers marking rows 1 to 5. At each turn the player has to uncover two cards. If they are matching, the cards are removed and the player can uncover a new pair of cards, and so on. Players switch turns

when a non-matching pair is uncovered. The game ends when all matching pairs have been discovered. The player with the most pairs wins.

The robot cannot manipulate the cards by itself. Instead, it says the letter and number of the desired card position, and then the user has to uncover it, enabling the robot to recognize the image of the card.

At each turn the players' performance is calculated based on the number of times uncovering a card in the same spot on multiple turns. At the end of the game the user's task performance is calculated based on the number of pairs.

The information about the players is stored in the EM-ART with 5 channels: Person, Game Difficulty, Robot turn, Performance, and Card. An event in the episodic memory corresponds to a turn in the game and an episode corresponds to a complete game.

The experimental conditions were defined by two factors, game difficulty level and presence of the robot. The game was tested with two levels of difficulty depending on the numbers of cards: 10 for the easy mode, and 20 for the difficult mode. Each participant played the game 3 times alone in both game modes before playing versus the robot, and 1 time versus the robot in each game mode.

2.3 Robot Behaviors

The robot has eight behaviors: Greeting people, pointing to the cards, and expressing pride, shame, admiration, reproach, encouraging, and judging. Except for encouraging and judging, each behavior produces both speech and movement. For pride, the robot rise its arms at the height of its waist, for shame, the robot rise its right arm and cover its face with it, for admiration, the robot "claps" with its arms, and for reproach the robot moves its head from left to right and vice versa two times. At each turn and at the end of the game, the robot can perform a body motion behavior or speak according to the intensity of the emotions present in its internal state. Fig. 1 shows the emotional expressions of admiration and pride corresponding to the actions of agents of the OCC Model.

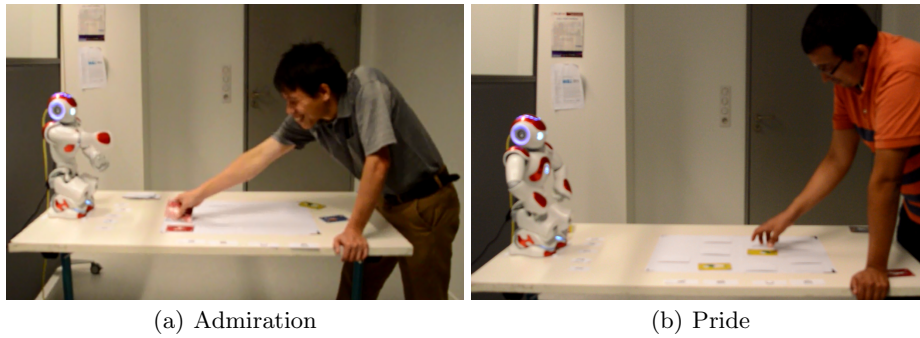


Fig. 1. Robot Emotional Expressions

3 Methodology

The high level framework proposed is composed of face and card recognition modules, an episodic memory, a cognitive emotional system, a task specific module to play the "Find the pair" game, a database of the preferences of the robot, and an expression generator module.

The face recognition module generates a search in the episodic memory specified by the name of the person and the game level difficulty, which gives the information of the last played game, and it is sent to the speech generation module. Based on the performance on the task (e.g. "number of pairs obtained") and the attitude of the robot towards the person and the game, the emotional system generates responses that are communicated to the expression generator module.

Face Detection is done by using the Viola-Jones [13] method and Face Recognition with Local Binary Patterns [1], using the implementations provided by the OpenCV library. Card Recognition is based on FindObject2D¹, an open source project that uses a bag-of-words approach with different types of 2D image features. Here, FindObject2D is configured to use the OpenCV implementation of FAST [11] features on images incoming from the robot's camera.

The game board used was a white paper of A3 size, with 4cm wide square corners coloured in black and set on a white table. For detection of the game board, the image was binarized with the Otsu method, and the Harris corner detection method was applied. Then, the region was transformed to correct perspective distortion and facilitate recognition of the cards. Game board detection and perspective correction was also implemented with OpenCV.

3.1 Episodic Memory

Our framework uses the EM-ART implementation presented in [4]. The EM-ART model [14], shown in Fig. 2, is made of three layers: Input, Events, and Episodes. The Input Layer is used to represent the external context information. It is categorized in channels in which each node represents the presence of a known element with an associated activation level (e.g. "Person A", "Easy Mode", "Card 1"). The nodes found in the Events Layer represents elements in the Input Layer that were activated simultaneously (e.g., "Person A" and "Card 1"). Synchronization of input elements is done by a short term memory buffer. As time progresses, the activation level of nodes in the Event layer decreases. Therefore, the sequence of events is represented by the pattern formed by those levels: the highest activation level is associated the most recent event to occur, and the lowest to the oldest. The Episodes Layer is made of nodes that categorize the patterns of the activation level of nodes in the Events Layer, thus defining episodes as temporal sequences of events. New episodes are created only when learning is triggered. In this work, learning is triggered at the end of each game to record its final sequence of events.

¹ <http://introlab.github.io/find-object/>

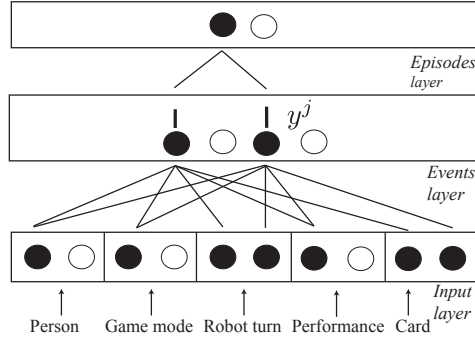


Fig. 2. EM-ART Model with a recalled episode built out of 2 events. y^j represents the activation level of event j .

3.2 OCC Model

The OCC Model [8] is based on 4 global variables and 12 local variables, each variable depending on both physical and psychological factors. The model has 22 emotions that are divided in three categories: *Aspect of Objects*, *Action of Agents* and *Consequences of Events*. In this work, we focused on the category of Action of Agents for its relation with the social facilitation effect. The synthesis of the emotions belonging to this category is described as follows:

Synthesis of Emotions. Let $A(p, o, t)$ be the approving of action o that person p assigns at time t . This function returns a positive value if the performance of the action is above the standards for that action, and returns a negative value if the action doesn't meet the standards. The standard is a given value to determine if the performance is low or high. Let $I_g(p, o, t)$ represent a combination of the global intensity variables. Let $P_a(p, o, t)$ be the potential for generating a state of admiration. If the action is performed by others, the rules for admiration and reproach are presented in Algorithm 1.

The approving function f_p is denoted by:

$$f_p = (Praise * SoR * CogUnit) + (Prox * a) + (Ar * b) \quad (1)$$

where *Praise* is the praiseworthiness, *SoR* is the sense of reality, *CogUnit* is the cognitive unit, meaning the grade of similarity between the preferences of the robot and the person, *Prox* is the proximity, *Ar* is the arousal and a and b are factors of increment set empirically to 0.1 and 0.3, respectively. The emotions of pride and shame were synthesized the same way, but based on the performance of the robot. The functions describing the arousal and the mood are presented in Algorithm 2. The threshold functions were denoted by a sigma function (2), and having as input the value of the mood. Also the arousal was processed with a s-shaped sigmoid function to limit its value.

Algorithm 1 Synthesis of Admiration and Reproach

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set  $P_a(p, o, t) = f_p(A(p, o, t), I_g(p, o, t))$ 
if  $A(p, o, t) > 0$  then
  Given a threshold value  $T_a$ 
  if  $P_a(p, o, t) > T_a(p, t)$  then set  $I_a(p, o, t) = P_a(p, o, t) - T_a(p, t)$ 
  else set  $I_a(p, o, t) = 0$ 
  end if
else
  Given a threshold value  $T_r$ 
  if  $P_a(p, o, t) > T_r(p, t)$  then set  $I_r(p, o, t) = P_a(p, o, t) - T_r(p, t)$ 
  else set  $I_r(p, o, t) = 0$ 
  end if
end if

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Algorithm 2 Arousal and Mood

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 $arousal = arousal + \sum_{i=1}^n intensity\_emotion - (t_i - t_{i-1}) * 0.05$ 
if  $arousal < 0$  then  $arousal = 0$ 
end if
if admiration or pride or love then
   $mood = mood + intensity\_emotion - (t_i - t_{i-1}) * 0.01$ 
else [reproach or shame or hate]
   $mood = mood - intensity\_emotion - (t_i - t_{i-1}) * 0.01$ 
end if

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The value of *Praise* is defined by $Praise = performance + (expDev)$, where $expDev$ is the expected deviation given by $expDev = performance - lastPerformance$. Then the *Praise* was processed with a sigma function denoted by:

$$y = (g / (1 + e^{-(x-x_0)/s})) + y_0 \quad (2)$$

where s is the change step of the sigmoid, g is the maximum value, x_0 is the half of the sigmoid, y_0 is used to give a positive or negative output and x is the input.

The parameters of the OCC Model were set up as: *Appealing* = 0.5, *Familiarity* = 0.1, *Praiseworthiness* = Player's performance, *Strength of Cognitive Unit*=1 for the robot's actions and 0.5 for the person's actions.

4 Results and Discussion

The experiment was done with a NAO robot from Aldebaran Robotics. The experiment was tested with 10 participants: 8 male and 2 female with ages in range from 22 to 34 years old and all with technical background. 4 of them had no prior interaction with a robot.

The measure of the performance for the Social Facilitation experiment was given by $perform = errors/pairs_obtained$, where *pairs_obtained* is the number

of pairs obtained at the end of the game. An error is counted when a card has been shown previously and the person did not remember its position. The results are presented in Table 1. Paired T-Tests for dependent means and two-tailed hypothesis were applied. The results were significant with $p < 0.10$, rejecting the null hypothesis for comparison between the Easy level played alone and the Easy level played with robot conditions ($t = -1.8653$, $p = 0.0950$) and for comparison between the Difficult level played alone and the Difficult level played with robot conditions ($t = 2.2003$, $p = 0.0553$). With $t < 0$, this suggests that the mean errors count in Easy mode was higher for the “playing alone” group (0.1788 vs. 0.0990), and the opposite in Difficult mode (0.3159 vs. 0.4810).

The differences in means are small, but can be explained by the small number of participants in the experiments. However, the results are statistically significant, and they confirm both hypotheses considered in this work. As expected for the theory of Social Facilitation, the performance is affected by the presence and behavior of the robot, improving it when the task is easy and worsen it when the task is difficult.

Table 1. Mean and variance of participants’ performance in the 4 game modes

	Easy Alone	Difficult Alone	Easy with robot	Difficult with robot
mean	0.1788	0.3159	0.0990	0.4810
var	0.0019	0.0211	0.0254	0.0837

The internal emotional states of the robot are presented in Fig. 3, where the performance of the robot and one participant in difficult mode can be seen. In Fig 3(a), when the performance of the participant turns negative (under the standard), the intensity of reproach increases. On the other hand, when the performance of the participant increases, the intensity of admiration increases too. In Fig. 3(b), the performance of the robot along with the emotions of pride and shame can be observed. Even when pride was called during the game, at the end the raised emotion was shame because the standards were set to expect a high score of the robot. The mood and the arousal of the robot in this game are shown In Fig 3(c), where the mood can take negative values according to the synthesized emotions based on the performance of both players, decreasing with time and with negative emotions as shame and reproach, and increasing with positive emotions as pride and admiration. The arousal only has positive values, increasing with any kind of emotions, and decreasing at a higher rate than the mood.

The emotion system was analysed using a subjective measure of the participants with a post-experiment questionnaire ². Table 2 (Robot Behavior) shows the answers of the participants on a 7-point Likert scale, 7 for strongly agree

² <http://goo.gl/forms/3TNI4KjvXu>

and 1 for strongly disagree (4 for neither agree or disagree). The answers of the participants show a clear recognition of the states of the robot in the different emotional states, which proves that the behaviors used were perceived as expected.

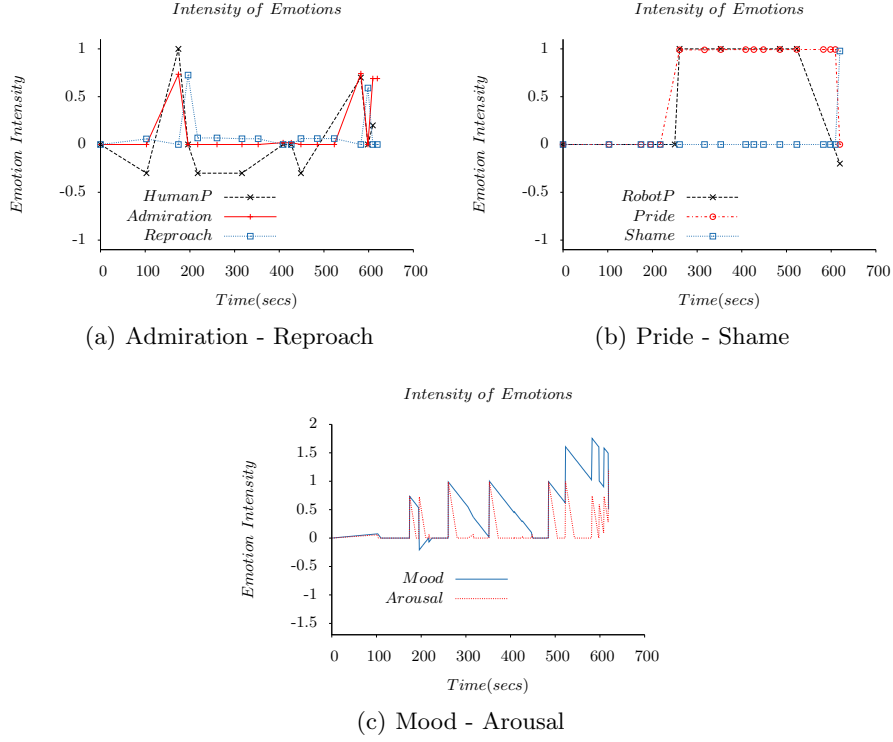


Fig. 3. Human and Robot Performance and Robot's internal state of Mood and Arousal

The negative mood was not so present due to the fact that even when the person gets a pair in the game, the robot can show admiration and increase its positive mood. Also, the participants were asked two questions about their level of appreciation of the game in both modes (easy and difficult). The answers are shown in Table 2 (Game Mode), which are related to the variable *CogUnit* of the OCC Model. If the values of the attitude of the players towards the game had been used, the intensity of the generated emotions should have been higher, because they are more similar to the set value in the robot's preferences.

Finally, two open questions were asked to the participants to express their liking or disliking towards the robot, multiple answers were allowed. 5 participants liked the enthusiasm of the robot, 3 participants liked the correlation between the actions and the behaviors, 4 participants found the robot funny,

and 1 participant found it clever. Six participants said that they disliked that the robot was too egocentric. This can be explained due to the fact that we wanted that the person feel being evaluated in the difficult mode.

Table 2. Participants’ feedback

Robot Behavior	mode	mean	var
1. Robot as good motivator in the easy game	6	4.62	2.92
2. Robot disturbing in the difficult game	3	3.67	2.60
3. Positive mood when it was winning	6	5.83	0.69
4. Negative mood when it was losing	2,3,5	3.58	2.99
5. Admiration when in the easy game	4	3.75	3.47
6. Reproach in the difficult game	6	4.50	2.63
7. Pride when it was winning	7	6.17	0.69
8. Pride when it was losing	3	2.92	1.90
9. Could be a good companion	6	5.50	1.72
10. Reproach when it was winning	4	3.67	3.33
11. Disturbing in the easy game	4	3.92	3.71
12. Motivating in the difficult game	4	3.67	2.60
Game mode	mode	mean	var
1. Easy	6	4.91	2.29
2. Difficult	6	5.82	0.76

5 Conclusion and Future Work

In this paper we investigated the social facilitation experiment in a human-robot interaction, with an emotional system based on the OCC Model. The results showed proofs reinforcing this theory, which makes us believe that this should have to be considered for companion robots where the interaction in everyday life can provoke stressful situations for the humans. This kind of robots have to adapt to their users through their interaction, and an emotional system can take place to manage the robot’s behaviors. For that reason, we plan to continue with the implementation of the OCC Model, which is a very extensive model that include a large range of emotions, where memory plays an important role. The EM-ART needs to be combined in a deeper way with the emotional system, because memory is the base of the section “consequences of events” of this model. Furthermore, an hybrid emotional approach, combining basic and cognitive emotions, may be beneficial for faster responses of the robot.

Acknowledgements The first author thanks to the Mexican Council of Science and Technology for the grant CONACYT-French Government n.382035 and to the Secretary of Public Education of Mexican Government for the support fellowship.

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