Psychophysiological Interaction and Empathic Cognition for Human-robot Cooperative Work (PsyIntEC)

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Abstract. The aim of the PsyIntEC project is to explore affective and cognitive modeling of humans in human-robot interaction (HRI) as a basis for behavioral adaptation. To achieve this we have explored human affective perception of relevant modalities in human-human and human-robot interaction on a collaborative problem-solving task using psychophysiological measurements. The experiments conducted have given us valuable insight into the communicational and affective queues interplaying in such interactions from the human perspective. The results indicate that there is an increase in both positive and negative emotions when interacting with robots compared to interacting with another human or solving the task alone, but detailed analysis on shorter time segments is required for the results from all sensors to be conclusive and significant.

Key words: human-robot interaction, psychophysiology, affective modeling, robotics

1 Introduction

The target industrial scenario of the PsyIntEC project is that of a small to medium enterprise engaged in rapid prototyping of novel devices. Production is typified by one-off assemblies or small batch runs of prototypes that often go through several iterations, customer specifications vary widely, and engineering and technical staff are few and have both diverse tasks and highly developed expertise. The one-off or small batch prototyping workshop application is one in which robot systems are not typically used, due to the excessive time and cost of programming and hardware configuration in relation to the small numbers of produced units.

Prototype production frequently requires much more cognitive problem solving on the fly during production than highly pre-planned, larger scale production runs, often with many prototype iterations investigating new components and configurations. Unlike mass production lines, workstations need to be flexible and support human engineers in performing diverse tasks for which they may have highly variable skills.

Uncertainties are much greater during prototype development, and this creates greater emotional and attentional demands upon human workers. The PsyIntEC project focuses upon demonstrating the feasibility of robotic guidance, support and facilitation of collaborative human-robot prototype production. It emphasizes support for human emotion and attention regulation, modulation and assessment (e.g. maintaining optimum levels of human attentional engagement in the task at hand) during cooperative human-robot task performance, based upon the use of psychophysiology data to measure human affective, emotional and cognitive states.

The first step in generating behavioral adaption in robots based on affective states in human co-workers is to understand the affective queues present in the interaction. By doing so, we can possibly use that knowledge to detect, and let the robot act according to the presumed state in the interaction.

1.1 Tower of Hanoi

The Tower of Hanoi (ToH) puzzle was selected as the reference task for the study. The reasons are that it is an easy task for a robot arm to handle, there exists an optimal solution, and solving the puzzle is a reasonable challenge for most humans. ToH is originally a single player game, and in collaborative gameplay the human-human or human-robot take turns to complete the game.

ToH is a mathematical puzzle game consisting of three rods, and a number of disks of different sizes that can slide onto any rod. The goal of the puzzle is to start from a given configuration of the disks on the leftmost peg and to arrive in a minimal number of moves at the same configuration on the rightmost peg. The puzzle has the following rules [1]:

- Only one disk may be moved at a time.
- Each move consists of taking the upper disk from one of the rods and sliding it onto another rod, on top of the other disks that may already be present there. A disk can also be placed on an empty rod.
- No disk may be placed on top of a smaller disk - i.e., disks are only allowed to be moved to empty rods or be placed on top of larger disks.

1.2 Hardware System

The hardware system contains two Adept Viper S650 [3] 6 DOF robot arms with Robotiq Adaptive 2-finger Grippers [4] as end effectors. The robot arms are controlled using an Adept SmartController CX control box and two Adept Motionblox-40-60R power adapters. The end effectors are controlled using two Robotiq K-1035 control boxes. An overview of the hardware platform used in the human-robot work cell is shown in Fig. 1.

[3] `http://www.adept.com/products/robots/6-axis/viper-s650/general` [Accessed 27/05/2013 09:09]

[4] `http://robotiq.com/en/products/industrial-robot-gripper` [Accessed 27/05/2013 09:11]

For psychophysiological measurements a Biosemi ActiveTwo [5] system with sensors measuring electrocardiography (ECG), electromyography (EMG), galvanic skin response (GSR) and electroencephalography (EEG) is used. A Microsoft Kinect camera is used to track the moves made by a human or robot during a ToH game. A single PC running Windows 7 is controlling the system.

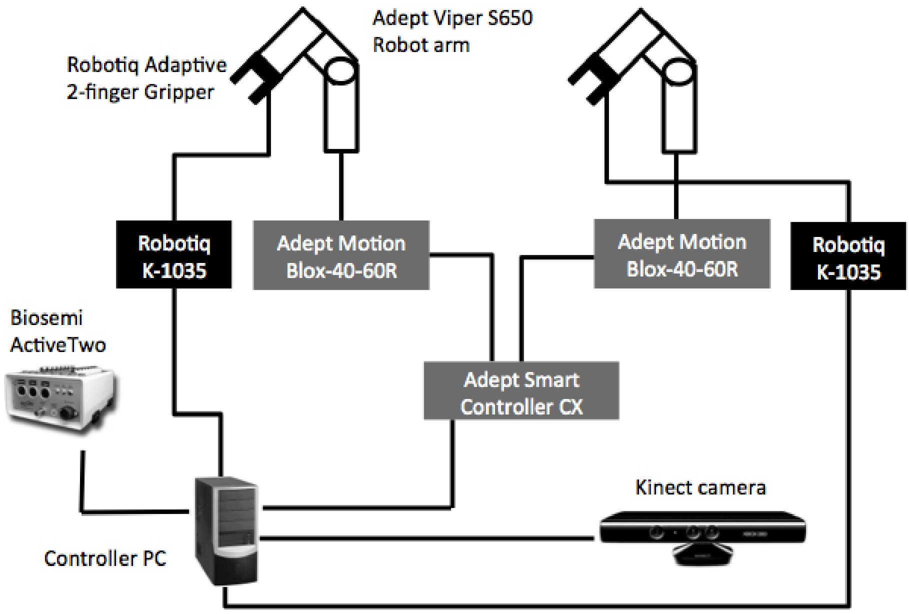

Fig. 1. Overview of the hardware system.

An overview of the software system is shown in Fig. 2. The *Action Module* is the core of the software system. It decides what move to make and when to make it. The *Scene Module* provides information about the moves made and which player is next to make a move. All move events (move made and timestamp for the move) are stored to disk using the *MoveLogging Module*. The *RobotControl Module* is responsible for executing a move. It involves how to move the robot arms to pick up and drop the specified game disk, and when to close/release the grippers. The *Scene Module* uses Microsoft Kinect SDK [6] to connect to the Kinect camera, and the EmguCV [7] (a C# version of OpenCV) library to construct a scene of the current game state. The *Robot-*

[5] `http://www.biosemi.com/products.htm` [Accessed 27/05/2013 09:12]
[6] `http://www.microsoft.com/en-us/kinectforwindows/develop/overview.aspx` [Accessed 27/05/2013 09:14]
[7] `http://www.emgu.com` [Accessed 27/05/2013 09:14]

Control Module uses the Adept ACE software [8] to control the robot arms. *ActiView* [9] is the data recording software for the Biosemi ActiveTwo system, which all sensors are connected to.

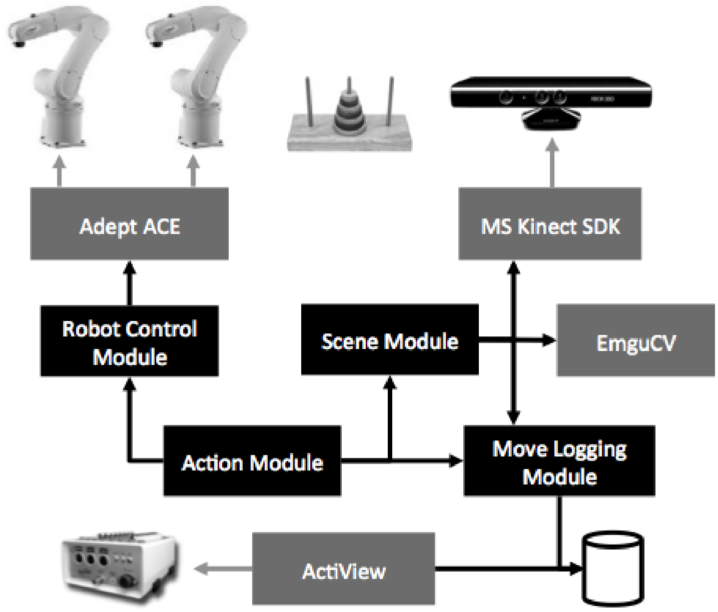

Fig. 2. Overview of the software system. Gray boxes are third-party libraries/modules.

1.3 Research Question and Method Overview

The goal of our study is to find out which types of sensors may be useful in creating a human-robot workstation that uses bio-feedback to adapt to the human emotions as measured by the sensors. Thus, our main question in this first study is to show which psychophysiological sensors are effective in terms of measuring differences between solving a puzzle task with or without the help of robots.

We limit this question by testing a selected set of sensors on the task of cooperatively solving ToH. This is done by conducting experiments with four different conditions as illustrated in Fig. 3. The first condition is a human completing the reference task alone, the second human-human collaboration and the third and fourth human-robot collaboration. In the fourth condition the robot is unpredictable in terms of speed and path

[8] `http://www.adept.com/products/software/pc/adept-ace/general` [Accessed 27/05/2013 09:15]

[9] `http://www.biosemi.com/software_biosemi_acquisition.htm` [Accessed 27/05/2013 09:16]

taken when moving the disks. In the experiments continuous measures of ECG, EMG, GSR and EEG were recorded during the completion of the reference task. The dependent variables involved quantitative measurements for evaluating task performance and psychophysiological emotional and qualitative measurements for checking perceived emotions.

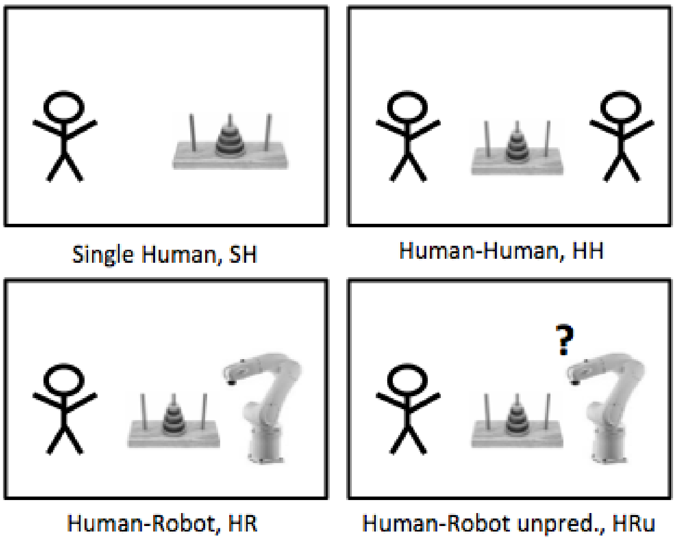

Fig. 3. Illustration of the four conducted experiment conditions. The order varies between participants.

2 Psychophysiological Measurements

In psychophysiological measurements, a number of different sensors can be used to measure physiological response to emotional states. In the PsyIntEC project ECG, EMG, GSR and EEG have been used. Below is an overview of each sensor type and how it can be used in emotion detection.

2.1 Electromyography

Facial EMG measures voltage levels on the surface of the skin on the locations of facial muscles involved in the generation of affective facial expressions, as an indication of emotional valence (pleasure to displeasure). Increased activity over the cheek (zygomaticus major) and periocular (orbicularis oculi) muscle regions increase with positive valence, while EMG activity over the brow (corrugators supercilii) muscle region increases with negative valence and decreases with positive [2]. A study by Janke showed substantially reduced EMG activity associated with inwardly-directed anger, compared with a group expressing induced anger [3]. This was interpreted as providing support for the view of Fridlund that facial expressions of emotion express information rather than necessarily reflect all felt emotion [4].

2.2 Galvanic Skin Response

Galvanic skin response (GSR) measures skin conductance as an indication of emotional arousal, attention, alertness and effort. Wu et al. showed an average detection accuracy of 45-73% for negative emotions and 62-78% for positive emotions using 30 extracted features [5]. There is also some evidence of GSR being a relatively strong indicator of negative emotions but fewer correlations have been found for positive emotions [6]. GSR measurements are taken from the surface of the skin, where electrical conductivity is affected by sweat released by eccrine sweat glands in response to physiological and emotional arousal. GSR includes short-term phasic responses to specific stimuli, and relatively stable, longer-term tonic levels. GSR may be measured in terms of resistance, conductance, or absolute voltage [6]. Measurements are typically taken from the palm of the hand, the fingers, or the soles of the feet, where eccrine sweat glands are most densely distributed, providing the strongest signal variations. One drawback with the use of GSR in the field is its susceptibility to influences of temperature, humidity and mechanical pressure at the points where sensors are attached.

2.3 Electroencephalography

Electroencephalography (EEG) measures electric activity of the brain that reaches the scalp, indicating cognitive/conscious states of attention, alertness and drowsiness. The interpretation of EEG data has largely been framed in terms of specific frequency bands associated with different cognitive and emotional states [6]: alpha waves (8–13 Hz) with relaxation, reflection and inhibition; beta waves (14–30 Hz) with alertness, anxiety, concentration, mental and physical activity; delta waves (0.5–3.5 Hz) with deep sleep; theta waves (4–7 Hz) with drowsiness, pleasure, displeasure, idling and inhibition; kappa waves (10 Hz) with thinking; and gamma waves (resting frequency around 40 Hz, modulated by 3–5 Hz) with cross-modal perception and perceptual recognition. Evidence suggests that stronger alpha waves in the right frontal hemisphere are associated with withdrawal (negative emotions), while those in the right frontal hemisphere are associated with approach (positive emotions) [2].

2.4 Electrocardiography

Electrocardiography (ECG) measures the rate and regularity of heartbeats by detecting the peaks of the highly positive R-waves in the signal [7]. It also measures other things like the size and position of the heart chambers, but that is irrelevant for our purposes here. A study by Malmstrom et al. used heart rate and skin conductance (GSR) to measure arousal when watching a stressor motion picture film [8]. The study showed a correlation with arousal, closely paralleling skin conductance variations. A study by

Drachen et al. showed a correlation between heart rate and arousal (excitement) in video game players [9]. Increased heart rate is a good indicator of arousal, especially for negative emotions [6]. Ya et al. showed over 90% detection accuracy of both positive (joy) and negative (sadness) emotions for multiple subjects based on ECG recordings [10].

3 Experimental Setup

A crossover study with controlled experiments was conducted in a laboratory setting. Lighting and temperature was controlled and the laboratory room had minimal distraction from the outside. Subjects were seated in a chair with fixed height and a predefined position. The height and position were constant during all experiment sessions in order to be able to compare the data between different sessions. Two experimenters were always present in the laboratory room to monitor the experiments, but they were completely hidden behind a screen and were instructed to be as quiet as possible. The presence of the experimenters was for safety reasons when using the robot arms and to monitor that all data were recorded correctly. Surveillance of the robot arms and subject was done using live feed from a video camera. In addition the robot control software included an emergency stopping sequence that would be triggered if defects in the program execution were detected.

The GSR, EMG and ECG signals were recorded using the Biosemi ActiveTwo system using active electrodes. The electrodes were prepared with conductive gel and attached to the participant as follows:

Table 1. The placement of the electrodes used for the GSR, EMG and ECG signals.

Signal	Placement
EMGC	Corrugator supercilli (eyebrow)
EMGZ	Zygomaticus major muscles (edge of the mouth)
ECG	Sternum top (chest)
	Sternum bottom (chest)
GSR	Medial phalanx (middle joint on left index and ring finger)
Ground /	Earlobe
Reference	Zygomatic bone (cheek bone)

The EEG signals were recorded using Biosemi ActiveTwo system and Biosemi Headcap with active electrodes [10]. In the experiments EEG signals from left and right frontal, central, anterior temporal and parietal regions (F3, F4, C3, C4, T3, T4, P3, P4 positions according to the 10–20 system and referenced to Cz) were used, in total eight channels. Anderson and Sijercic used 6 channels in [11], Ying et al. also used 6 channels [12] and Petrantonakis and Hadjileontiadis only used 3 channels [13]. A Microsoft Kinect camera was used to monitor the moves made by the humans and, in human-robot collaboration, the robot arms. The camera software stored a log file with

[10] `http://www.biosemi.com/products.htm` [Accessed 27/5/2013 09:17]

a timestamp for each move, which move was made, and if the move was optimal (ToH has a mathematically optimal solution) or not.

The system used the ActiView recording software to record and store data from the Biosemi ActiveTwo system. ActiView, the robot control software and the Kinect camera software were running on the same computer in order to sync timestamps between the different data files.

All experiments were recorded using a digital camcorder placed in front and to the right of the participant and elevated to get a better overview of the experiment. The camcorder was equipped with a microphone that provided the opportunity to record utterances from the subject during the experiments in the attempt to model the oral communication between the subject and experimenter or vocalizations when the subject was alone. The same camera was also used for surveillance of the subjects and robot arms in case of any emergency.

The experiments were carried out at the Robotics and Cognition laboratory at Blekinge Institute of Technology, Karlskrona, Sweden. The Ethical Review Board in Lund, Sweden, approved all experiments (reference number 2012/737).

3.1 Experiment Procedure

A demonstration of the setup is shown in Fig. 4. It shows one of the authors sitting at the human-robot work cell with all the sensors attached.

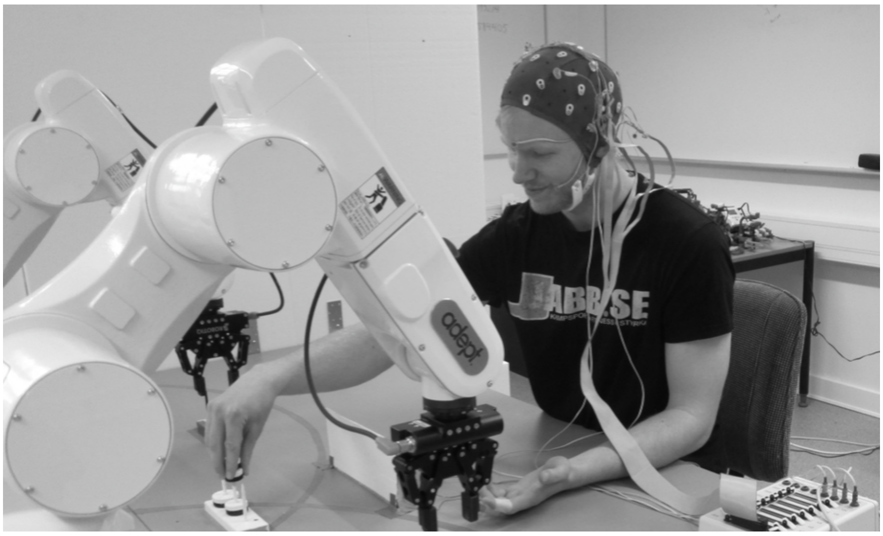

Fig. 4. One of the authors demonstrating the experimental setup.

Upon arrival, the participant followed a documented procedure in order to give all participants the same treatment as far as possible:

1. After entering the lab room each participant was seated in a fixed chair at the table and faced the game task at 50–60 cm distance.
2. The participants were given written information about the experiment and a description explaining the Tower of Hanoi puzzle. Before starting the experiment session, the participants played a practice ToH game with three disks in order to get them acquainted with the task. They were also given written information explaining psychophysiological measurements and that the data was stored anonymously. When the participants agreed to take part in the experiments they signed an informed consent form.
3. Before the experiment started participants filled in a questionnaire that included questions about age, their familiarity with the Tower of Hanoi task, board games in general, and solving mathematical problems.
4. The psychophysiological sensors measuring ECG, EMG, GSR and EEG were attached. Participants were asked to relax for four minutes in order to acquire a baseline for the psychophysiological data.
5. Each participant performed an experiment with four conditions: SH, HH, HR and HRu. The order of the conditions was varied between participants in order to minimize ordering effects. Each experiment condition was conducted as follows:
   (a) The participant played a ToH game while continuous measures of psychophysiological data and video were recorded.
   (b) After a game was finished, the participant was asked to mark his/her emotional state on the Geneva Emotion Wheel (GEW) [14]. The purpose of GEW is to log the subjective feelings of the subjects during the experiment period.
   (c) The operator instructed the participant about what task to perform next by showing information signs on a laptop placed next to the subject. The operator controlled the laptop using remote desktop.

For each of the four conditions, the participant played the ToH game three times (thus in all, a total of 12 games were played for each participant). Each experiment took around 90 minutes to complete. Note that the analysis of the GEW is out of scope for this part of the study.

In total 70 subjects participated in the study. 58 were male and 12 female. Ages varied between 19 and 31 with a mean of 23.6. The participants were students at Blekinge Institute of Technology and were recruited by advertisement in the university corridors and by recruiting during lectures. Each participant received a cinema ticket (worth approximately €9) for participating in the study.

4 Data Processing

The psychophysiological data was used to estimate the emotional states of each participant according to the two-dimensional valence and arousal scale. *Valence*, describing if the emotion is negative, positive, or neutral, and *arousal*, describing the physiological activation state of the body ranging from low to high.

Each participant data set was checked for errors. Errors were usually caused by problems like participants that did not completely understand the rules of the ToH game, or failure of one or more sensors. This caused whole or parts of the data to be invalid, for some participants. More specifically, 5% of the EMG currogator, 13.2% of the EMG zygomatic, 17.7% of the EEG, 6.1% of GSR, and 21.4% of ECG.

The signals were recorded continuously from when the sensors were attached to the subject and until the experiment ended. To analyze the relevant data, a segment for each game (three games per condition x and participant i) and a segment for the baseline period were extracted from the signals and the rest of the data (from waiting periods between games) were discarded. The first minute of the baseline period was skipped to remove initial non-relaxed activation in subjects. For the rest of the baseline period, a baseline value $b_{i,s}$ was calculated for each sensor s. The ECG data was an exception and was further processed to extract the heart rate before the baseline was calculated. To compare psychophysiological data between participants several signal features were extracted [13, 15]. The features used are mean value, minimum value, maximum value and standard deviation.
For a condition x and a sensor s, the mean values $\overline{v_{x,s}}$ are defined as follows:

$$\overline{v_{x,s}} = \frac{1}{N} \sum_{i \in N} \frac{1}{|G_x|} \sum_{g \in G_x} (\overline{v_{i,g,s}} - b_{i,s}) \tag{1}$$

where N is the total number of individuals participating in the experiments, G_x is the set of games using condition x, $\overline{v_{i,g,s}}$ is the average of the values of sensor s in game g with participant i, and $b_{i,s}$ is the baseline value for i and s. The maximum value $v_{x,s}^{max}$ is calculated in the following way:

$$v_{x,s}^{max} = \max_{i \in N} \max_{g \in G_x} (\max(v_{i,g,s}) - b_{i,s}) \tag{2}$$

The minimal value is calculated in a similar way:

$$v_{x,s}^{min} = \min_{i \in N} \min_{g \in G_x} (\min(v_{i,g,s}) - b_{i,s}) \tag{3}$$

We will focus on analyzing the overall mean, minimum, maximum, and standard deviation values for each condition. Note that the minimum value is the smallest observable value in a condition, and maximum is the largest observable value. Analysis of the first and second difference is out of scope for this part of the study. Averages can be used to detect systematic changes over time, although it might miss specific spikes in otherwise relative low activity since these are averaged out. To compensate for this, minimum and maximum values were included, since the magnitudes of the largest spikes (positive and negative) are given by these. To show an example of an EMG zygomatic signal, see Fig 5.

5 Data Analysis

For each data segment the mean, minimum and maximum for each sensor were calculated and the baseline (average activation of the baseline period) was subtracted. A data segment is the sensor signal data measured during one ToH game. Each subject therefore has three segments for each condition SH, HH, HR and HRu (three games were

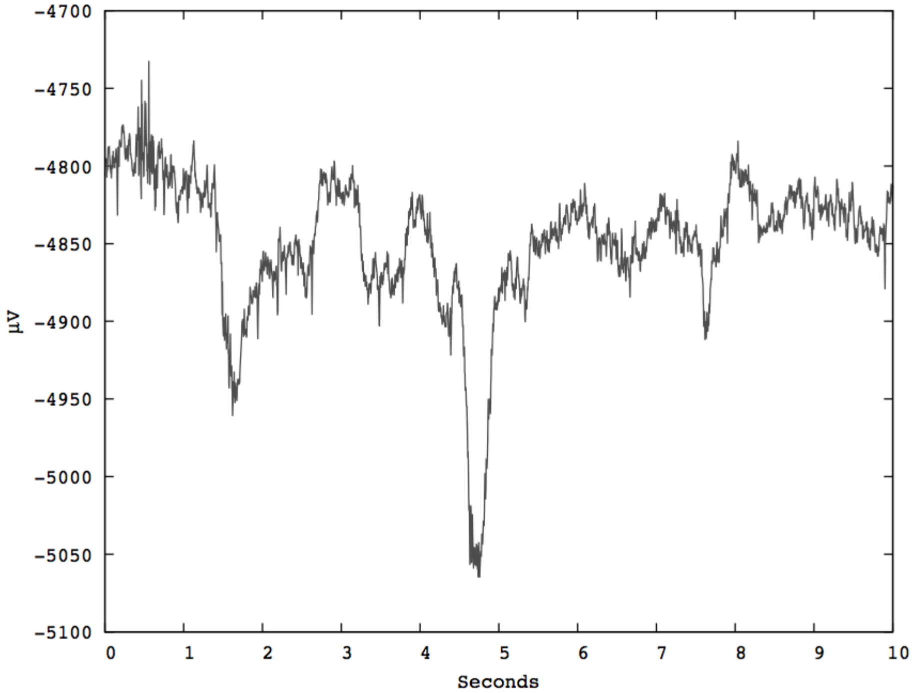

Fig. 5. A EMG zygomatic recording from one subject.

played in each condition). The mean, min and max values for all eight EEG sensors were averaged to get single values for EEG activation.

The values for each condition were then averaged over all 70 subjects. Each condition has in total 210 data segments (70 participants and three data segments per participant). The average values over all data segments were then compared between the four different experiment conditions. The results are presented in Table 2.

The averages that differed between the conditions were calculated using one-way analysis of variance (ANOVA), and are presented in Table 3. A problem with this is that ANOVA assumes that the observations should be independent of each other, which is not the case here since the same people played all four conditions. The ordering effects are averted (or at least minimized) by having different orders of the various conditions, but they are still not independent of each other. To lower the risk of committing a type I error (i.e. to detect a difference where there actually is none), the more stringent $\alpha = 0.01$ was used in the analysis.

5.1 EMG Corrugator

The activity levels for the EMG sensor placed on the corrugator muscle are shown in Fig. 6. Increased activity is a good indicator for negative valence (see Section 2.1). The results indicate almost equal levels for SH, HH and HR with increased activity for HRu.

Table 2. The averages of all participants' sensor data, as well as the overall minimum and maximum for each sensor and each condition.

Sensor	SH Avg	SH StdDev	SH Min	SH Max	HH Avg	HH StdDev	HH Min	HH Max
EMGC	1894	4311	-9055	11060	1938	4277	-9251	11947
EMGZ	1583	3540	-5308	9665	1105	3111	-6421	8502
GSR	846.8	811.8	-985.5	3447.1	1130	774.3	-525.2	3227.6
Heart rate	2.816	5.911	-11.46	21.74	2.300	5.384	-12.44	15.26
EEG	919	2431	-3937	6600	1166	2523	-3948	7687
	HR Avg	**HR StdDev**	**HR Min**	**HR Max**	**HRu Avg**	**HRu StdDev**	**HRu Min**	**HRu Max**
EMGC	1997	4051	-6443	11740	2439	4623	-7989	11966
EMGZ	1092	3555	-6931	9759	1498	3898	-6818	9853
GSR	767.7	896.6	-1281.2	3302.6	688.1	874.3	-1433.5	2791.4
Heart rate	1.427	5.783	-12.97	19.86	0.4977	4.638	-11.08	13.10
EEG	1146	2586	-3287	7425	1212	2576	-3899	7790

Table 3. One-way analysis of variance (ANOVA) for the normalized sensor values, significant values at $\alpha = 0.01$ marked with *.

Sensor	Significance
EMG corrugator	0.564
EMG zygomatic	0.405
GSR	0.000*
Heart Rate	0.001*
EEG	0.716

Table 4. Post-hoc analysis using Fisher's least significant difference for Heart Rate and GSR, significant values at $\alpha = 0.01$ marked with *.

Sensor	Experiment	Experiments HH	Experiments HR	Experiments HRu
GSR	SH	0.001*	0.348	0.062
	HH		0.000*	0.000*
	HR			0.345
Heart Rate	SH	0.393	0.022	0.000*
	HH		0.146	0.003*
	HR			0.122

This may suggest that the unpredictable robot behavior can produce negative emotions. The differences are however not significant, see Table 3.

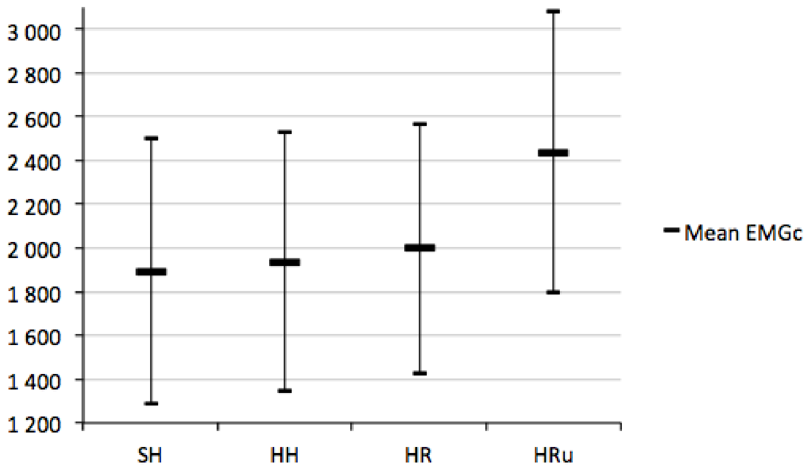

Fig. 6. Mean value (with confidence interval) for the EMG corrugator for the four different experiment conditions.

5.2 EMG Zygomatic

The activity levels for EMG over the zygomatic muscle are depicted in Fig. 7. Increased activity is a good indicator for positive emotions (see Section 2.1). The results indicate equal activation levels for HH and HR and increased activity for SH and HRu. This may suggest that playing alone compared to playing with an experimenter produces more positive feelings, maybe due to fear of performing badly when collaborating with an experimenter. The EMG corrugator results also indicated increased activity for HRu, suggesting that playing with the unpredictable robot can produce both positive and negative emotions. As in the case of EMG corrugator, the differences are not statistically significant (see Table 3).

5.3 GSR

The activity levels for the GSR sensor are shown in Fig. 8. GSR is a strong indicator of arousal, especially for negative emotions (see Section 2.2). The results show high activation when playing with another human (significant at the $\alpha = 0.01$ level, see Table 4), suggesting high arousal, and almost the same activity levels for the other game types. This might be an indication of increased negative stress for subjects when playing with an experimenter, as also indicated by the results from EMG zygomatic.

5.4 ECG

The raw ECG signal was processed to extract the heart rate activity (pulse) in beats per minute. This is shown in Fig. 9. Heart rate activity is a good indicator of arousal for both positive and negative valence (see Section 2.4). The results show small, but in

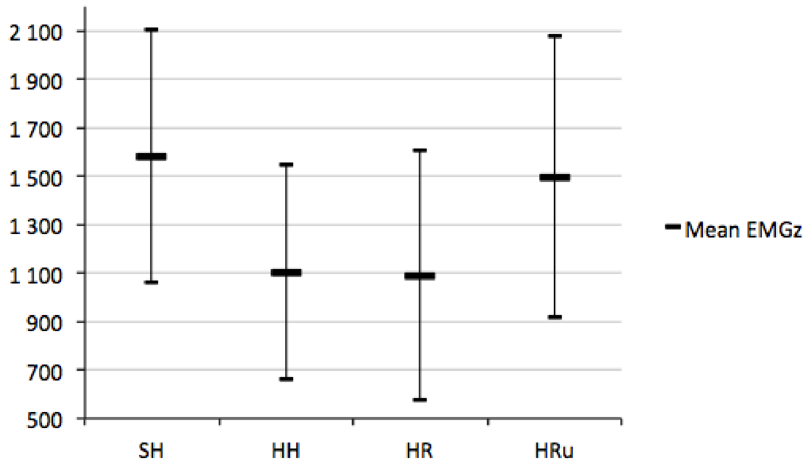

Fig. 7. Mean value (with confidence interval) for the EMG zygomatic for the four different experiment conditions.

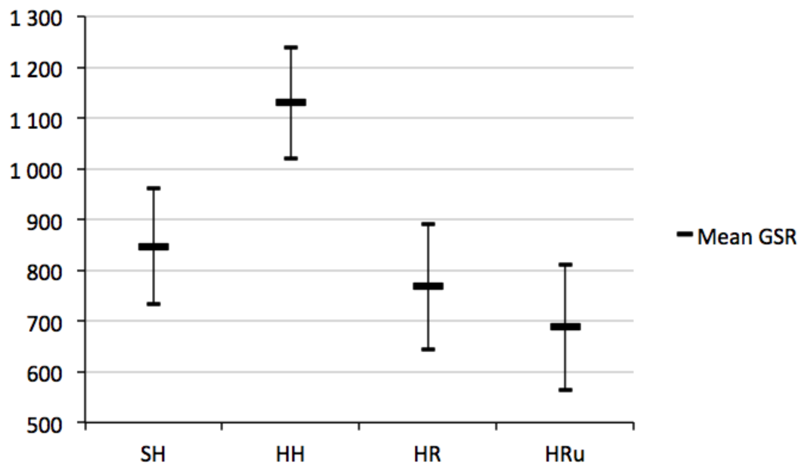

Fig. 8. Mean value (with confidence interval) for the GSR for the four different experiment conditions.

some cases significant differences between the conditions where the heart rate in the single human condition is slightly higher than in the robot collaboration conditions. There is also a significant difference in the comparison between HH and HRu, where the subjects show a higher mean heart rate when playing together with another human, compared to playing with the robot (see Table 4 for an overview). This is an indication of increased arousal when playing alone or with another human, compared to playing with robots. This can be an indication for subjects feeling calmer when playing with robots, relying on the robots to ”do the work”.

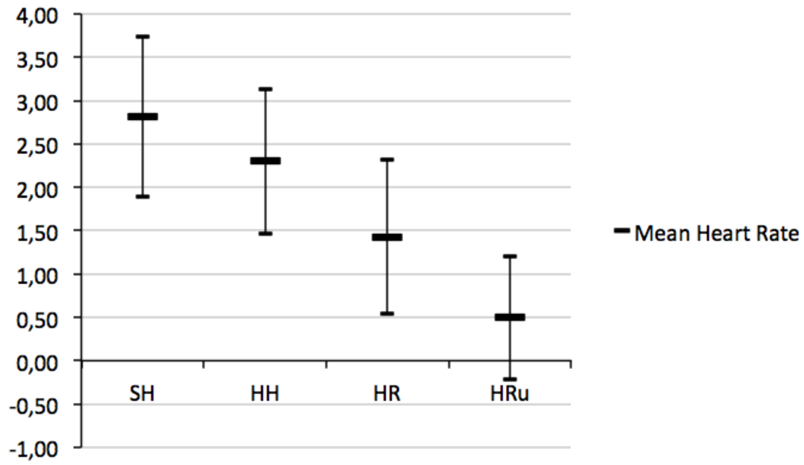

Fig. 9. Mean value (with confidence interval) for the Heart rate activity for the four different experiment conditions. Note that the values are normalized w.r.t. the baseline.

5.5 EEG

The EEG activity levels averaged over all eight sensors are shown in Fig. 10. The results indicate quite similar activity levels for HH, HR and HRu and a slightly decreased activity for SH. This suggests that all tasks where the subject has to collaborate with either a human or robots require increased attention and cognitive activity (see Section 2.3). However, there are no statistically significant differences, as can be seen in Table 3.

6 Discussion, Conclusions and Future Work

The results presented in this part of the study are from playing a complete Towers of Hanoi game. A game often lasts several minutes and averaging the activity of a sensor over such long time periods can disguise short-term activity variations.

The two EMG sensors showed clear differences between playing alone or with another human compared to the unpredictable robot. This suggest that playing with the unpredictable robot can produce both positive and negative feelings in subjects, the differences are however not statistically significant. It is reasonable to assume that the differences are through spikes of activity, rather than slow changes. This would mean that if the EMG sensors registered high activity during short periods of time, much of

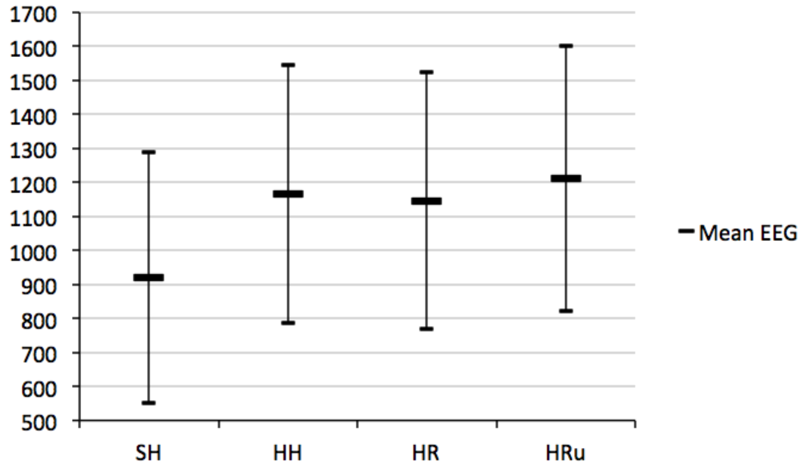

Fig. 10. Mean value (with confidence interval) for the EEG for the four different experiment conditions.

that would be lost when averaging over the whole condition due to resting periods between the spikes. A more detailed analysis on shorter time intervals is needed to see short-term changes in emotional states.

The EEG sensors showed increased attention and cognitive load for all collaborative tasks, but no differences were shown between collaborating with a human or robots. As for the EMG sensors, the differences in EEG activity are not statistically significant.

The heart rate activity showed small but significant differences between the game types, with a decrease in activity for HRu compared to playing without robots. This is an indication of increased arousal when playing without robots, but does not say if positive or negative emotions were produced.

The GSR showed a significant increase in activity when playing with a human experimenter. This is a sign of increased arousal, maybe due to fear of performing badly. It does however not say if the feelings experienced were positive or negative.

The data analysis performed cannot clearly answer the research question of what psychophysiological sensors are effective in terms of measuring differences in affective states between solving a task with or without robots. The EMG sensors indicated a difference but the results are not statistically significant when we look at the average values alone. The results from the heart rate and GSR sensors were significant but showed no clear difference between playing with or without robots. The EEG sensors might be indicators of collaborative or non-collaborative tasks. Analysis of the other features (first and second difference) and on shorter time intervals is needed to better answer the research question and these interesting analysis will be future topics of research. Our results do however give indications that EMG for valence and GSR/heart rate for arousal are effective in measuring affective states in human-robot interaction.

A possible future work is to cut the data into one segment for each move to be able to do analysis for shorter time intervals. This will show the activity levels in more detail and may give insights into how affective states change throughout a game. There is also the possibility of analyzing the video recordings (video and sound) to see when participants show emotions and do detailed analysis of the data from those time periods.

Another possible future work is to correlate the psychophysiology data to the subjective feelings of participants as stated in the GEW forms. This could give valuable insights into whether participants that subjectively felt stressed in the human-robot interaction also experienced increased psychophysiological activity and therefore possibly show stronger correlations in the data between playing with or without robots.

The next step in the PsyIntEC project is to develop a human cognition and affect model (a form of knowledge base) based on the experiment results. The model will have real-time automated state updates based upon data inputs from biometric interfaces. The purpose is to detect changes in affective states in the human co-worker. An analysis of the data on shorter time intervals is needed to develop this model.

The cognition and affect model will then be used to develop an adaptive robot decision model to complete reference tasks while optimizing human safety, job satisfaction/engagement and task performance. Robot performance parameters will be modified in real time based upon the human affect model.

A future experiment is planned to compare the human affective perception of the adaptive robot decision model compared to the human-robot and human-robot unpredictable conditions used in the experiments described in this part of the study.

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