When to engage in interaction - and how?
EEG-based enhancement of robot's ability to sense social signals in HRI

Stefan Ehrlich[1], Agnieszka Wykowska[1,2], Karinne Ramirez-Amaro[1], and Gordon Cheng[1]

Abstract— **Humanoids are to date still limited in reliable interpretation of social cues that humans convey which restricts fluency and naturalness in social human-robot interaction (HRI). We propose a method to read out two important aspects of social engagement directly from the brain of a human interaction partner: (1) the *intention to initiate eye contact* and (2) the distinction between the observer being *initiator or responder* of an established gaze contact between human and robot. We suggest that these measures would give humanoids an important means for deciding *when (timing)* and *how (social role)* to engage in interaction with a human. We propose an experimental setup using *iCub* to evoke and capture the respective electrophysiological patterns via electroencephalography (EEG). Data analysis revealed biologically plausible brain activity patterns for both processes of social engagement. By using Support Vector Machine (SVM) classifiers with RBF kernel we showed that these patterns can be modeled with high within-participant accuracies of avg. 80.4% for (1) and avg. 77.0% for (2).**

I. INTRODUCTION

In everyday lives, humans are embedded in rich social environments. It is typical of humans to seek social contact, which is intrinsically very rewarding [1], [2]. In this respect the willingness or intention to be engaged is a crucial aspect of social interaction. Humans are capable of expressing and detecting this intention by many subtle and mainly non-verbal social cues, such as touch, gestures, and body posture. Gaze is one of the most important social signals, as it is often involved in initiation of social contact and engagement [3].

Humanoid robots in contrast are to date still severely limited in this respect. It is perhaps mostly due to the subtleties of these signals that make their interpretation based on visual, auditory and tactile sensors so challenging. This issue is particularly thwarting the applicability of humanoid robots in areas where social interaction with humans is crucial, such as in elderly- and healthcare, household robotics, and social robotics in general [4], [5].

In this work, we propose a method that bypasses the interpretation of these cues and instead aims at reading out human intentions directly from the brain in form of electrophysiological signals (EEG). We focus our research on two basic, but very important aspects of social engagement whose prediction from electrophysiological signals we believe will significantly help enhancing social human-robot-interaction (see Figure 1):

- The *intention to initiate eye-contact* for entering into social engagement with others, in our case the humanoid *iCub*. This measure is crucial for natural and efficient onset of interaction [3]. The ability to sense this measure would give a humanoid a means of deciding *whether and when* to engage in social interaction with a human.
- The distinction between the observer being *initiator or responder* of the gaze contact. This distinction is crucial for the pleasantness and shape of the further course of interaction [6]. The ability to sense this measure would give a humanoid a means of estimating its *social role* during the interaction. This estimate will help the robot to adapt its behavior according to the expectations of the human interaction partner.

The rest of the paper is structured as follows: Section II introduces related work. Section III describes our proposed experiment setup for evoking and capturing the related electrophysiological responses. In Section IV we present our signal processing and modeling approach. In Section V we discuss the work and its implications on social HRI. Section VI concludes the work.

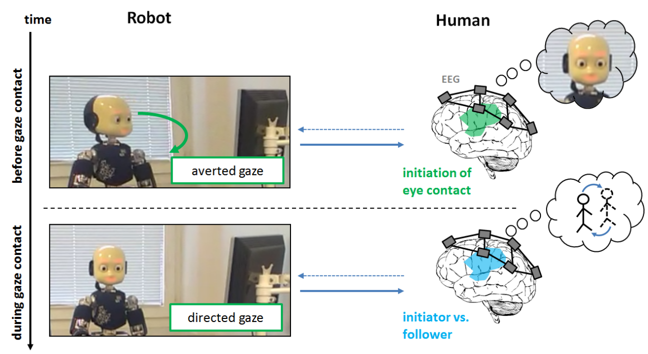

Fig. 1. Two processes of social engagement: initiation of eye-contact for onset of interaction (top) and distinction between initiator versus follower when eye-contact is established (bottom).

II. RELATED WORK

The approach of utilizing implicit measures from electro- or psychophysiological signals for human-computer-interaction (HCI) is a relatively young sub-field of Brain-Computer Interface (BCI) research and commonly referred as *passive BCI*. In contrast to ordinary BCIs, in which users are requested to voluntarily and consciously modulate their

[1]Gordon Cheng (department head), Stefan Ehrlich, and Karinne Ramirez-Amaro are with the Institute for Cognitive Systems (ICS), Technische Universität München, Germany. stefan.ehrlich@tum.de

[2]Agnieszka Wykowska is with the Experimental Psychology Unit at the Department of Psychology, Ludwig-Maximilians-Universität München, Germany and associated with the Institute for Cognitive Systems (ICS), Technische Universität München, Germany.

brain-activity to control a computer device, passive BCIs aim for continously providing valuable information about the user's state (emotional responses, intentions, motivations) to the technical system - most of the time not to the awareness of the user [7]. Many works reported so far are focused on applications in the field of *gaming and entertainment* [8]. Gilleade *et al.* described in 2005 an approach in which the level of difficulty in a computer game was adapted based on the psychophysiological measure heart rate [9] in order to maintain optimal challenge for the player. Another field is referred as *adaptive automation (AA)* in which a task is dynamically alocated between user and machine. In 1992 Yamamoto *et al.* described a system which constantly monitored drowsiness via galvanic skin response (GSR). If arousal dropped an alarm sound was played that indicated the user to increase concentration [10]. This field of application is particularly interesting for the automotive sector with respect to driver monitoring for safety reasons. Not much work has been found in the area of *social human-robot-interaction*. However, one particularly interesting work has been presented by Szafir and Mutlu in 2012 [11] in which a humanoid appeared as a story narrator in front of human participants. Based on a measure of vigilance/attention acquired by EEG, the robot adapted its level of gesticulation, mimics and gazing during storytelling. The study showed that this inference could positively influence the vigilance level in participants who were then significantly better in recalling details of the story after the experiment.

III. EXPERIMENT

A. Objective

The purpose of this experiment was collecting electrophysiological data related to two aspects of social engagement: the *intention to initiate eye-contact* and the distinction between the observer being *initiator or responder* of the gaze contact. In order to evoke and capture these responses, our experiment made use of a *belief manipulation* that intended to make participants believe that they were able to willfully influence the robot's behavior (provoking the robot to engage in social interaction with them). Once captured, the respective EEG patterns can be identified and translated into predictive models ultimately applicable in social HRI in line with the passive BCI approach. Note, that this experiment was not a passive BCI approach, but a preliminary study to collect data with the purpose of developing a passive BCI.

B. Environment and data recording

The experiment took place in a quiet room which was partitioned into two sections by means of a movable wall. On the right side of the room, a participant was seated on a comfortable chair approximately 2 meters in front of the humanoid iCub (see Figure 2). iCub is a 53 degrees of freedom humanoid [12] which has an in-build control unit communicating with an external workstation via local network based on TCP/IP. For the robot control and thus the implementation of the experiment protocol we used Yarp [13] and iCub [14] libraries. Furthermore, we equipped the robot with a speech synthesis system by including the package iSpeak, which acquires sentences over a yarp port and lets the robot utter them. The robot was arranged as if standing behind a table and looking at a computer screen (see 2, top).

The left side of the room was reserved for the experimenter monitoring the experiment protocol and a live-visualization of the recorded EEG data. For EEG data recording we used a separate PC. Besides controlling the robot, the robot workstation is further responsible for sending, in specific moments of the experiment protocol, event-triggers via parallel port (LPT) to the EEG amplifier. These triggers appear in the EEG data as event-codes facilitating later segmentation of the data. EEG data was acquired with a BrainProducts actiChamp amplifier equipped with 32 active EEG electrodes arranged according to the international 10-20 system. All leads were referenced to Cz and sampling rate was set to 500 Hz. The impedance levels of all leads were kept below 10 kΩ. The amplifier is battery-driven and was located on a tray nearby the participant. The data was transferred via USB to the recording PC. Participants were given earplugs for minimizing auditory distractions. Speech and beep-indications were played back via Logitech stereo desktop speakers with an appropriate loudness. The participants were asked to sit still, but comfortably during the experiment and try to move as little as possible.

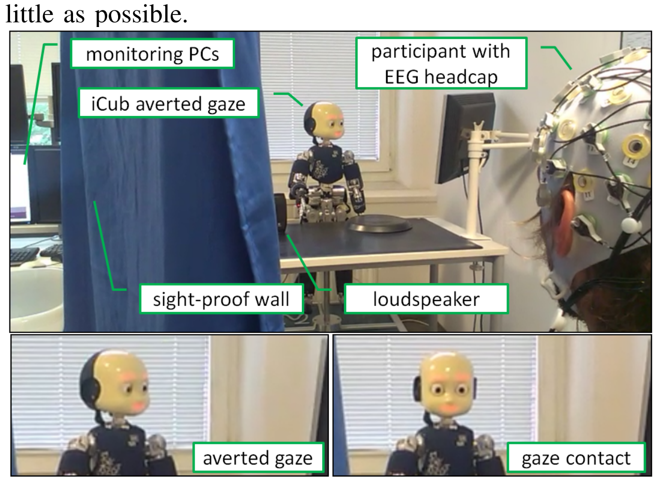

Fig. 2. Top: experiment setup with participant. Bottom: iCub attending computer screen (averted gaze) versus iCub establishing gaze contact with participant.

C. Experiment protocol

In our experiment the robot was attending a computer screen to its left side for most of the time. This was realized with a neck angle of 42°, the robot's torso was directed towards the participant. Our experiment was arranged in a trial-based fashion with consecutive gaze-contact events. Figure 3 illustrates one such a trial. Each trial started with a 5 seconds pause, indicated by the auditory spoken cue "break till beep!". Then a beep-tone occured which indicated exactly one upcoming gaze-contact event to the participant. The gaze-contact event followed within a random-time between 5-8 seconds after the beep and had a total duration of 3 seconds: First, the robot turned its head to 0° neck angle

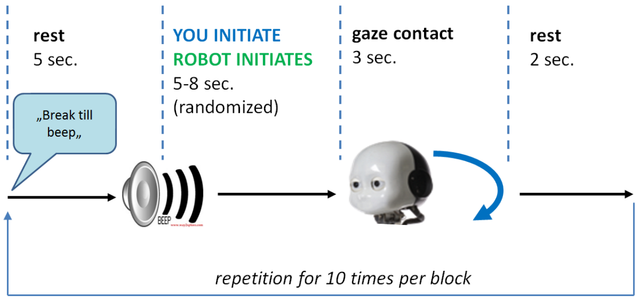

Fig. 3. One trial consists of an initial rest of 5 sec. followed by a 5-8 sec. task depending on the condition. Afterwards follows the gaze-event of 3 sec. duration. The trial ends with another resting period of 2 sec. The trials are repeated for 10 times per block.

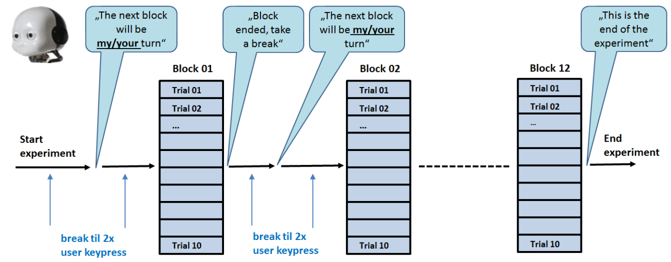

Fig. 4. One block consists of 10 gaze-contact events (trials) under one of both conditions "YOU INITIATE"/"ROBOT INITIATES". The participant will be informed verbally about the type of interaction prior to the start of the next block.

with an angular velocity of 50°/s and lowered its gaze by -5° in order to meet the eyes of the participant (parameters were calibrated prior to the start of the experiment). After approx. 3 seconds the robot moved back its head and eyes to the initial position. The gaze-contact event was followed by another break of 2 seconds. Each trial had a duration of 15-18 seconds.

The trials were arranged in a block-wise fashion of 12 consecutive blocks; one block consisted of 10 trials and gaze-contact events respectively (see Figure 4). We introduced two conditions (types of interaction with the robot) which alternated randomly from block to block. The randomization was controlled such that no more than 2 consecutive blocks would belong to one condition. The two conditions were:

- "YOU INITIATE" interaction: The participants were instructed that we have built an algorithm capable of extracting relevant information from their EEG signals that is associated with the *intention to initiate eye-contact* with an interaction partner. The participants were told that this algorithm worked in real-time and influenced the robot's behavior based on the participants will to engage in social interacion with the robot. Participants were instructed that whenever the beep-tone occured in the "YOU INITIATE" blocks they would be able to willfully influence the robot's behavior (provoking the robot to look at them).
- "ROBOT INITIATES" interaction: The participants were instructed that in this condition the above-mentioned information was not provided to the robot (connection was turned off). The robot would be rather entering the social interaction on its own *"intention"*. Participants were instructed that whenever the beep-tone occurs in the "ROBOT INITIATES" blocks they just had to await the robot gazing at them.

Unbeknownst to the participants **no such an algorithm existed**, hence the blocks were entirely identical, the gaze-contact always followed within a random time in between 5-8 seconds. With this belief-manipulation we aimed to evoke brain activity patterns specific for the intention to engage into social interaction. Participants could self-pace the start of each new block: After hitting a specific key on a keyboard they first received verbal instruction from the robot speech synthesis system about the type of interaction in the next block ("The next block will be **your** turn!" for the "YOU INITIATE" condition; "The next block will be **my** turn!" for the "ROBOT INITIATES" condition). After hitting another key the next block started. The total duration of the experiment was approx. 45 minutes. For the entire duration of the experiment the robot's facial expressions were set to happy.

The participants were first instructed (verbally and by means of written instruction) about the experimental setup and handed a questionnaire about personal details. To test whether participants believed the experiment instructions they were given another questionnaire after the experiment that included questions e.g. about how well they thought the robot responded to their intention to engage into gaze-contact.

D. Participants

Six healthy participants (age: 27.5±3.82, all males) participated in the experiment. The participants covered a variety of nationalities (China, Germany, Iran, Spain, Turkey) and thus a considerable spectrum of cultural background. Educational background was predominantly in engineering and computer science majors (5 out of 6 subjects). Prior experience and familiarity with humanoids varied widely among the participants and scored 4.17±1.57 on a scale of 1 "non-familiar" to 7 "familiar". All participants were equally instructed about the experiment setup and agreed on having their data acquired by signing a consent form. Each participant was paid a honorarium of 15 EUR.

IV. DATA ANALYSIS AND RESULTS

A. Questionnaire

In order to check if participants believed they could willfully influence the robot's behavior in the "YOU INITIATE" condition we asked them after the experiment how well they thought the robot responded to their intention to engage in eye contact. Participants rated 5.33±0.94 on a scale from 1 "non at all" to 7 "very well". Furthermore, we asked in which condition they felt generally more comfortable. No tendency could be observed as 2 of 6 participants rated ”YOU INITIATE”, 2 of 6 participants rated ”ROBOT INITIATES” and 2 of 6 participants rated ”no difference”. Participants were also asked in which condition they felt rather positive emotional responses during the gaze contact. The majority of participants (3 out of 6) rated that the ”YOU INITIATE” condition caused stronger positive responses (2 out of 6 rated ”no difference”). For negative emotional responses most participants rated ”no difference” (4 out of 6). All participants except for one found the experimental conditions corresponding properly to the instructions provided by the experimenter. The remaining participant missunderstood how the robot was actually supposed to react to the participant in the ”YOU INITIATE” condition, but still believed that he was able to willfully influence the robot. We therefore decided not to exclude his data from the analysis. The questionnaire responses indicated that all subjects appropriately believed the experiment instructions througout the experiment.

B. Preprocessing and artifact removal

Data preprocessing was carried out using BrainProducts BrainVisionAnalyzer (BVA). BVA comes with a set of inbuilt signal processing functions particularly relevant for EEG data preprocessing and visualization. During manual data inspection we noticed large voltage drifts in participant (p01) which were not simply to be filtered out. We therefore decided to remove this dataset from the analysis. For the remaining datasets we carried out the following steps: (1) We re-referenced each single EEG channel to the average of all leads and reconstructed channel Cz (originally used as reference). (2) We downsampled the data to 250 Hz to reduce processing time in all further steps. (3) We bandpass-filtered the data using a Butterworth zero phase IIR-filter with a low cutoff around 0.5 Hz and a high cutoff around 70 Hz (12dB/octave). (4) In the next step we manually cut out the data in between blocks as they did not contain any relevant information and might have negatively influenced the next steps of preprocessing. (5) We transformed the data to the component-level using 512 steps Infomax extended Independent Component Analysis (ICA). (6) Next, we manually selected those components which were most probably associated with eye-blinks, removed them and (7) transformed the data back to channel-level using inverse ICA. The data was then exported for further analysis in MATLAB.

C. Data segmentation

According to the purpose of the experiment, we aimed at exploring and modeling the electropsychological patterns of two specific processes of social engagement with a humanoid: (1) the *intention to initiate eye-contact* and (2) the distinction between gaze contact based on whether the human was the *initiator* or the *responder* of gaze contact. For both analyses we extracted and compared different segments of the EEG data using functions provided by the MATLAB EEGLAB toolbox:

1) Intention to initiate eye-contact: In order to compare and model the EEG patterns we contrasted them against an ideally perfectly clean baseline which we decided to take from the initial resting period in the trials of the ”ROBOT INITIATES” condition where no patterns related to intentions were assumed to be present. We decided to extract the latest 3 seconds of the resting-trials since the first second of the resting period might still be affected with auditory processing of the robot’s speech cue ”break til beep!”. With this processing step we obtained 60 *baseline* segments of length 750 samples per channel and participant. Based on our experimental design we assumed to find brain activity patterns for the intention to initiate eye contact directly after the beep-tone in those trials which were related to the ”YOU INITIATE” condition. In order to avoid biases in the data we decided to extract the same length of segments as for the baseline segments. We assumed to find the patterns best developed some time after the beep and decided to extract 3 second segments from the moment of 2 seconds after the beep and thereby obtained 60 *intention* segments of length 750 samples per channel and participant.

2) Initiator versus responder gaze contact: In this comparison we contrasted the 3-second periods of gaze contact of both conditions. Thereby we obtained 60 *responder* segments from the ”ROBOT INITIATE” condition and 60 *initiator* segments from the ”YOU INITIATE” condition, both of length 750 samples.

D. Feature extraction

Feature extraction was carried out identically for both above described comparisons. Each of the segments was first filtered into 5 frequency bands (standard frequency bands in EEG signal processing), by means of 2nd order zero-phase Chebyshev IIR-bandpass filters, namely theta (4-7 Hz), low alpha (7-10 Hz), high alpha (10-13 Hz), beta (14-30 Hz) and gamma (30-47 Hz). In preliminary analyses and visualization of the data we noticed distinct differences between low and high alpha bands and therefore subdevided this band into two subbands. For each filtered segment we then computed the log-variance as a measure of spectral power which is associated with band-specific cortical activation in EEG. For each segment/trial we thereby obtained one value as a means of cortical activation in a specific frequency band and channel. The features were then concatenated into one vector resulting in 160 features (32 channels x 5 frequency bands). The trials were then labeled according to the above described comparisons.

E. Data visualization and interpretation

For data visualization we computed the means over all trials and participants and visualized the 160 features in topoplots (see Figure 5). Despite the relative small number of participants we could observe quite interesting and plausible effects in the EEG patterns. For the comparison *intention vs. baseline* the strongest effect was a decrease of anterior and posterior alpha power which has been consistently reported in the literature in association with alertness and increased attention, e.g. in [15] (see Figure 5, top - a). In beta- and gamma-band we could observe a hemisphere lateralization with increased anterior gamma-power on the left side and decreased central beta-power (see Figure 5, top - b). Hemisphere lateralizations have been reported as reflecting approach and widthdraw motivation caused by differential activation of the medial prefrontal gyrus (MPF). For example, in 2005 Talati *et al.* [16] found greater left MPF activations for approach and greater right MPF for widthdraw tendencies. For the comparison *gaze-contact initiator vs. gaze-contact responder* the alpha-power effect was almost no more present, both conditions resulted in relatively similar alpha-activities. The left hemisphere activity in beta- and gamma-band were even more strongly pronounced than in the prior comparison (see Figure 5, bottom - c). We interpret this effect as to be related to some kind of amplification of the approach tendency mixed with activities related to processing of intrinsic reward in the ventral striatum (located in the limbic system below the pre-frontal cortex). Moreover, we observed power-decreases over left and right motor cortex (central) in high alpha band, which are typically associated with motor preparation and execution (see Figure 5, bottom - d). This supports the notion of pronounced approach motivation that already involves preparation of motor responses. We consider these findings as strong indicators that the acquired data is valid and contains the electrophysiological patterns we aimed to capture.

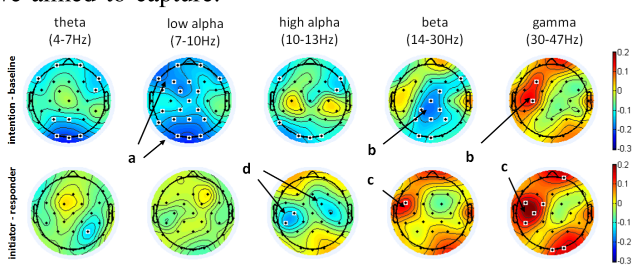

Fig. 5. Top: grand average over all participants *intention* minus *baseline*, strongest effects: anterior and posterior low alpha-power decrease (a); hemisphere lateralization for beta- and gamma-power (b). Bottom: grand average over all participants *initiator* minus *responder*, strongest effects: pronounced left hemisphere beta- and gamma-power increase (c); high alpha-power decrease over motor cortex (d). White markers indicate highest deviations between conditions.

F. Modeling

In order to create predictive models to discriminate the patterns we used Support Vector Machines (SVM) classifiers by employing the LIBSVM library by Chang *et al.* [17]. SVMs were developed for solving binary classification problems and model an optimal hyperplane for discriminating both classes. SVMs are particularly powerful as they find the best tradeoff between good generalization by simultaneously maximizing the performance and minimizing the complexity of the model. Moreover, SVMs can be used with kernel functions that map the features into high-dimensional space in which non-linearly separable data can be discriminated by linear hyperplanes. We assumed our data to be non-linearly separable and thus decided to employ a Radial Basis Function (RBF) kernel, which has also been consistently reported as the most suitable kernel for EEG-signal based classification problems, e.g. in [18]. Furthermore, we performed an exhaustive search to find optimal values for the learning parameter C and the kernel parameter γ. For SVM training we used all 160 features and evaluated the models in two ways:

- 5-times-5-fold participant-individual cross-validation (**CV**): The data from one participant is partitioned into 5 folds, 4 folds are used for training the SVM model and the remaining fold is used for testing. The folds are then shuffled until each fold had once been used for testing. The whole procedure is repeated for 5 times. The 5x5 results are averaged and reported as classification accuracy (see equation 1). This procedure was carried out for each participant individually.
- Leave-1-participant-out validation (**L1O**): The data from 4 participants were concatenated and used for training the SVM model. The data from the remaining participant was used for testing. The procedure was repeated until the data from all individual participants had once been used for testing. Identical to CV, the results are reported as classification accuracy.

$$accuracy = \frac{\text{\# correctly predicted data}}{\text{\# total testing data}} \times 100\% \qquad (1)$$

The results reported in Table I show that with the proposed approach a maximum participant-individual classification accuracy of 84.8% (p04) to predict the *intention to initiate eye contact* was obtained. On average we obtained a CV-accuracy across all subjects of 80.4%. For the L1O validation we obtained a maximum accuracy of 67.5% and an average accuracy of 64.2% across all subjects.

TABLE I

CLASSIFICATION ACCURACIES FOR *intention vs. baseline*

	CV			**L1O**		
participant	accuracy	C	γ	accuracy	C	γ
p02	83.8%	100	0.001	65.0%	0.1	0.005
p03	66.2%	2	0.1	66.7%	3	0.01
p04	84.8%	3	0.01	58.3%	0.001	2
p05	83.0%	20	0.001	64.2%	10	0.001
p06	84.0%	10	0.005	67.5%	0.001	0.005
AVG	80.4%			64.2%		

Table II shows the results for predicting whether participants were initiating or following gaze-contact with the robot. We obtained a maximum CV-accuracy of 84.3% (p05) and on average 77.0% across all participants. L1O-validation yielded a maximum accuracy of 71.7% and on average 61.0%. We did not observe any tendency regarding optimal values for the parameters C and γ.

V. DISCUSSION

Our data analysis revealed biologically plausible brain activity patterns that we have shown can be modeled offline with high within-participant (participant-dependent) and

TABLE II

CLASSIFICATION ACCURACIES FOR *initiator vs. responder*

	CV			L1O		
participant	accuracy	C	γ	accuracy	C	γ
p02	76.3%	100	0.001	60.8%	1	0.5
p03	69.2%	3	0.1	55.8%	0.001	0.005
p04	80.7%	10	0.005	71.7%	20	0.005
p05	84.3%	10	0.01	58.3%	20	0.001
p06	74.5%	2	0.05	58.3%	2	0.05
AVG	77.0%			61.0%		

promising across-participant (participant-independent) accuracies. In order to prepare and evaluate our models for utilization in online passive BCI-based HRI we suggest to consider the following steps which we aim to explore in follow-up research: So far, the modeling is based on data of a relative small number of participants. With 10 or more participants we would be able to identify the respective brain patterns more clearly. This would eventually lead to a reasonable selection of the most prominent regions and frequency bands prior to the modeling: We expect that feature selection / employment of sparse-classifiers will significantly enhance the generalization abilities of user-independent models, hence improve our L1O-validation results. Still, user-independent models might not work robustly with day-to-day variations and should therefore be equipped with adaptive capabilities. For online-evaluation an additional and different experimental design is required for which - in contrast to this study - we suggest to leave the participants unaware (unbiased) of the fact that a passive BCI is tested.

In line with the basic idea of passive BCI, it is crucial to point out that our approach is not meant to substitute any other modality of robot-perception (visual, auditory, tactile), but rather meant to augment the set of modalities by providing the robot additional access to implicit information about the human's intention and willingness to engage into interaction with the robot. We are confident that the introduction of the proposed predictive models in closed-loop with humanoids would significantly enhance the fluency, naturalness, and particularly the social aspects of interaction, specifically at the moments of onset and further development of the course of interaction. This will help to design better robot behaviors, in particular with respect to timing of the gaze controller to seek and keep engagement. Moreover, we believe that combining/fusing our proposed implicit measures from EEG signals with ordinary visual, auditory and tactile measures would eventually result in enhanced robot capabilities to reason about, and derive higher-level meaning of human intentions, actions, and behaviors. This would ultimately help predicting probable future actions which in turn enhances fluency and efficiency in human-robot interaction on a greater scale.

VI. CONCLUSIONS

This paper aimed at enhancing robot's abilities to sense when (timing) and how (social role) to engage in interaction with a human by means of EEG. We conducted an experiment to evoke and capture electrophysiological data (EEG signals) associated with (1) the intention to initiate eye-contact and (2) the distinction between initiator and responder role in established eye-contact with the humanoid iCub. Predictive models based on our offline data analysis and modeling approach achieved high within-participant classificiation accuracies of avg. 80.4% for (1) and avg. 77.0% for (2). Results for participant-independent models are above chance-level and promising. Our approach reaches across-participant accuracies of avg. 64.2% for (1) and 61.0% for (2).

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