Dataset documentation: Human-agent co-adaptation

Manuscript: Human-agent co-adaptation using error-related potentials
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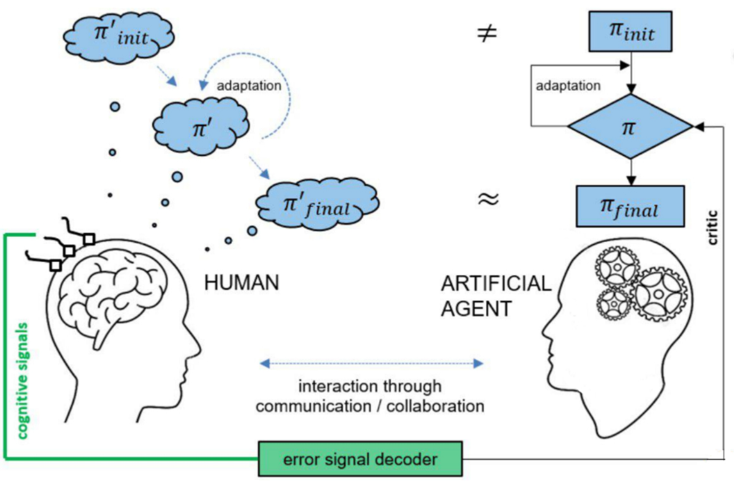
Introduction

This dataset was part of an experiment in which error-related potentials (ErrPs) were recorded using EEG from human subjects during human-agent interaction scenarios in order to mediate co-adaptation toward a consensus of both partners. In contrast to prior human-robot interaction scenarios there was no predefined superiority of the human partner over the robot. Both the human and the robot were required to adapt to each other and finally converge to a consensus in the given joint task.

Conceptual approach

When interacting with an agent, the human holds a mental model (belief) of the agent's policy π' in order to predict its future behavior, which is based on prior expectations π'_{init} and further adapted during interaction. ErrPs were decoded online from the neuronal activity of the human partner and provided a critique for guided adaptation of the agent's actual model. This created a two-party co-adaptive system allowing both the human and agent to seek consensus in the form of an alignment of the human's belief and the agent's actual policy $\pi'_{final} \sim \pi_{final}$



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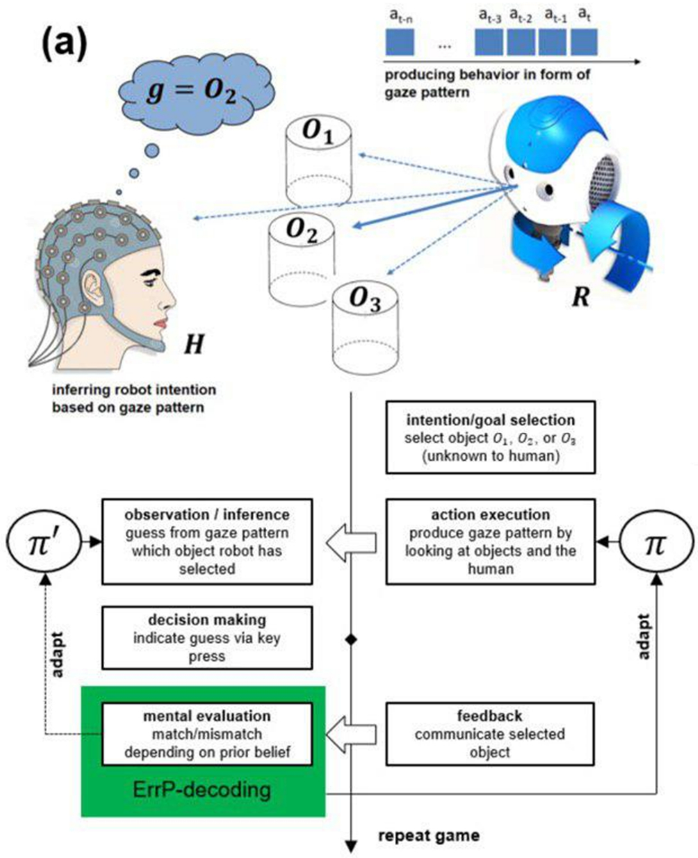
Implementation

The approach was implemented in a guessing game experiment whereby a human subject and robot covertly select one of three given objects. Subsequently the robot produces a gaze pattern from which the subject has to guess the secret object. The subject's brain responses are measured (marked in green) and used as a feedback signal to adapt the robot's gaze behavior policy. Throughout the experiment, the subject may also adapt his/her prior belief about the robot's gaze behavior policy. The overall system consists of three main parts: a human (1) who interacts with an artificial agent such as a robot (2) and a brain-machine interface used for decoding neurophysiological activity linking the two behaviors (3).



Human		Agent		Brian-Machine interface	
Number of participants	18 / (16) (data of two subjects had to be deleted due to technical issues)	Type	humanoid robot	Type	EEG
Age	29.2 ± 5.0 years	Hardware	Soft Bank NAO robot	Hardware	Brain Products actiChamp amplifier
Sex	7 female, 9 male	Specifications	21–25 degrees of freedom, pitch and yaw movement of head, three identical green light emitting diodes (LED) attached to head	Electrodes	32 active EEG electrodes; arranged according to 10–20 system
Honorarium	8 EUR/h				
		Feedback presentation	visually with attached LEDs on head, auditory by internal sound module	Referencing	average of TP9 and TP10
				EEG channels	FP1, FP2, F3, F4, F7, F8, FC1, FC2, FC5, FC6, C3, C4, T7, T8, CP5, CP6, P3, P4, P7, P8, TP9, TP10, O1, O2, Fz, Cz, Pz
		Software	single programm using Python-based NAOqi-library (robot control), the Phidgets-library (LED control), Psychopy library (keyboard and screen control)	EOG channels	EOG1, EOG2, EOG3 (forehead, left and right outer canthi)
		PC 1 (robot control)	Intel®Core™ i5 CPU 750@2.67 GHz.	Sampling rate	1024Hz
				Maximal Impedance	10kΩ
				Software	Matlab, OpenVibe
				PC 2 (EEG recording)	Intel®Core™ i5 CPU 750@2.67

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Experimental design

1. Experimental tasks:

Each experiment consisted of an open-loop calibration session (CALIB) which was followed by four closed-loop co-adaptation sessions (CORL-I to CORL-IV). Participants were asked to observe the robot and thereby guess the chosen objects from the robot's gaze behavior.

Part	Short name	Short description and purpose	Duration
1 Open-loop calibration session	CALIB	***Task:*** To guess the robot's selected object, indicating guess via key-press. ***# trials:*** 150 (3 blocks of 50 trials each) ***Purpose:*** Collect EEG data for subsequent calibration of subject-specific ErrP-decoders ***Robot gaze policy:*** pre-programmed and non-adaptive. Elicitation of ErrPs with random occurrences of false-feedback events with a probability of $p_{err} = 0.3$.	15–25 min
	ErrP decoder calibration	Automatic calibration of subject-specific ErrP decoder based on data collected during CALIB	5 min
2 Closed-loop co-adaptation sessions	CORL-I	***Task:*** To guess the robot's selected object, indicating guess via key-press. ***# trials:*** 50 ***Purpose:*** Online application of ErrP decoder for mediating human-robot co-adaptation ***Robot gaze policy:*** Initial uniformly random gaze behavior; updated after each trial based on the classified outcome of the corresponding online decoded ErrP	6–8 min
	CORL-II	Same as CORL-I with reinitialization of gaze policy	6–8 min
	CORL-III	***Task:*** To guess the robot's selected object *without* overtly indicating guesses via key-press (compared to CORL-I,-II, and -IV). Robot performed gaze behavior for a pre-defined fixed duration. ***# trials:*** 50 ***Purpose:*** Online application of ErrP decoder for mediating human-robot co-adaptation *without explicit decisions* from the human partner (sole observation and mental reflection upon the robot's gaze behavior) ***Robot gaze policy:*** same as in CORL-I,-II, and -IV with reinitialization of gaze policy	6–8 min
	CORL-IV	Same as CORL-I with reinitialization of gaze policy	6–8 min

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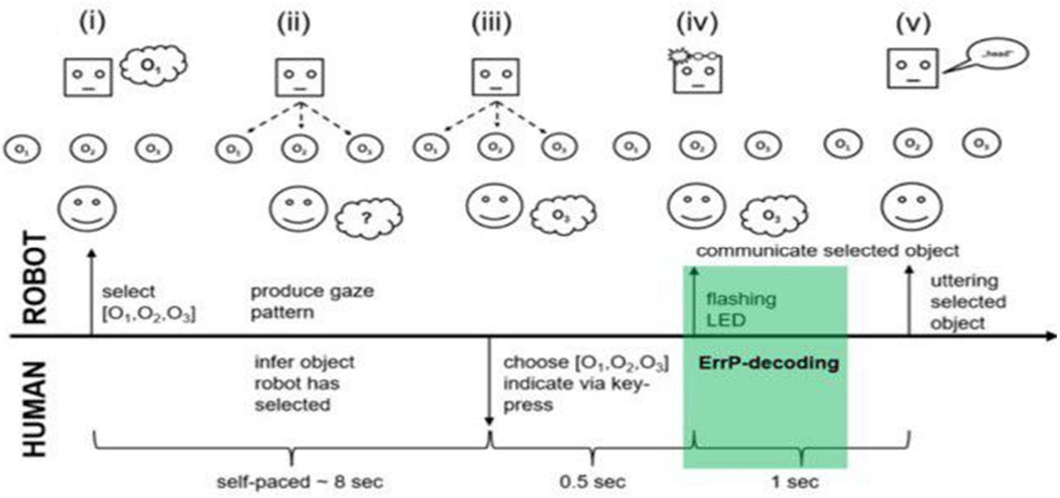
2. Trial structure:

One trial can be understood as one round of the guessing game and is divided in five chronological segments.



ID	DURATION	HUMAN	ROBOT
(I)			Gaze at human, random selection of one object and initial gaze state
(II)	~8 sec	Guess robot's choice from gaze pattern	Produce gaze pattern based on current policy
(III)	0.5 sec	Indicate the guess by a keypress	Stop gaze pattern and turn head back to human
(IV)	1 sec	Record EEG signal to detect ErrPs	Visually indicate selected object by LED blinking
(V)			Give auditory feedback about selected object

3. Goal selection, gaze policies and action execution

Before any action execution, the robot has to choose one of three possible goals/intentions $\boldsymbol{G} = \{\boldsymbol{g_{O1}}, \boldsymbol{g_{O2}}, \boldsymbol{g_{O3}}\}$. This selection was implemented as a uniform random choice. The robot's internal gaze policy was realized as a discrete state-space model with four states, $\boldsymbol{S_\pi} = \{\boldsymbol{s_{objInt}}, \boldsymbol{s_{othObjx}}, \boldsymbol{s_{othObjy}}, \boldsymbol{s_{human}}\}$ with s_{objInt}: gazing at selected object; $s_{othObjx}$, $s_{othObjy}$: gazing at one of the other objects; and s_{human}: gazing at human. An action $A_{i,j}\ with\ \ i, j = S_\pi$ is considered a transition from one gaze state to another or remaining in the current gaze state. The policy - $\pi(a_i \mid s_j) \in [0,1] \subset \mathbb{R}$ determined the gaze behavior described by the probability of taking action a_i in state s_j (gaze transition from state s_j to s_i). The decision for the next action was always performed by a weighted random selection among the four possible actions in the current state.

The robot gaze behavior resulted from a fixed mapping between the covert policy-states S_π and the overt action-execution states S_{act}, depended on the selected object:

$$S_{\pi\to act}\left(g_{O1}\right) = \left\{s_{objInt\to O1},\ s_{othobjx\to O3}, s_{othobjy\to O2},\ s_{human\to H}\right\},$$
$$S_{\pi\to act}\left(g_{O2}\right) = \left\{s_{objInt\to O2},\ s_{othobjx\to O3},\ \ s_{othobjy\to O1},\ \ s_{human\to H}\right\},$$
$$S_{\pi\to act}\left(g_{O3}\right) = \left\{s_{objInt\to O3},\ s_{othobjx\to O1},\ s_{othobjy\to O2},\ \ s_{human\to H}\right\}.$$

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Robot head angles were predefined for each action-execution:

Action	Pitch Ψ	Yaw Θ
s_{O1}: gazing at O_1	25°	-20°
s_{O2}: gazing at O_2	25°	0°
s_{O3}: gazing at O_3	25°	20°
s_H: gazing at Subject	0°	0°

4. Decoding ErrPs

For each subject, an individual ErrP-decoder was trained based on the data collected during the calibration session and later used in the online co-adaptation runs. The following steps were performed:

Signal filtering		Signal segmantation		Classification	
1	causal first-order Butterworth FIR bandpass filter; cutoff frequencies 0.5 and 20 Hz	4	data segmentation in epochs of [0,1] sec time-locked to the moment of presentation of LED feedback	6	labelling of calibration data for training
				7	extraction of temporal features
2	EOG activity reduction by a regression method	5	normalizing by subtracting the individual means for each channel and segment	8	data balancing by random pick and replace
3	re-referencing to common average			9	ten-fold grid search for optimal shrinkage parameter (λ∈[0,1] in steps of 0.05)
				10	training of final rLDA classifier (training set comprises all trials of CALIB session, pick and replace was repeated 1000 times and parameters of all classifiers were averaged for final rLDA)

5. ErrP-based agent policy adaptation

$$\pi^{t+1}(a_i|s_j) = \pi^t(a_i|s_j) + \alpha R \sum_{k=1}^{n} a_{i,j}^k \qquad (1)$$

π	The robot's policy
t	count of current trial
R	Reward from ErrP decoder (-1 or 1)
α	Learning rate (α = 0.1)
a_i	Action i
s_j	State j
$k=(1,...,n)$	Action sequence in current trial
n	Depending on subject's self-paced decision

For policy adaptation, a gradient method with the policy update function (1) was executed at the end of each trial during the co-adaptation runs. Truncation and normalization was performed after adding the policy gradient $\alpha R \sum_{k=1}^{n} a_{i,j}^k$ to the parameters of the old policy t: parameter updates of t+1 which exceeded the range $\{0,1\} \in \mathbb{R}$ were truncated to 0 and 1, respectively, and all actions per state were then normalized to sum up to one.

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Dataset structure

The Dataset is structured in the folders **data_cursor** and **data_coadaptation**, where each folder is further subdivided in the respective subjects **s****. The data itself is uploaded for each subject's session as **.fdt**, **.set** and **_log** files.

Folder/File			Folder/File		
data_cursor		cursor data of each subject	**data_coadaptation**		coadaptation data of each subject
s**		Subject number	**s****		Subject number
s_cursor**	.fdt .set	cursor data of Subject s**	**s**_calib**	.fdt .set .log	CALIB data of Subject s**
			s_corl1**	.fdt .set .log	CORL1 data of Subject s**
			s_corl2**	.fdt .set .log	CORL2 data of Subject s**
			s_corl3**	.fdt .set .log	CORL3 data of Subject s**

Trigger/Marker information in EEG data (data_coadaptation)

33025	NAO decision – left object (not communicated to subject)
33026	NAO decision – middle object (not communicated to subject)
33027	NAO decision – right object (not communicated to subject)
33028	Human decision left object (response key "1")
33029	Human decision middle object (response key "2")
33030	Human decision right object (response key "3")
33031	Feedback no error
33033	Feedback machine/human error
33034	NAO communicates chosen object via flashing LED
33035	NAO communicates chosen object via speaking out the name of the object
33036	NAO turns to object of interest
33037	NAO turns to other 1. object
33038	NAO turns to other 2. object
33039	NAO turns to human

Trigger/Marker information in EEG data (data_cursor)

33025	Presentation of stimulus – left
33026	Presentation of stimulus – up
33027	Presentation of stimulus – right
33028	Response arrow key – left
33029	Response arrow key – up
33030	Response arrow key – right

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33031	Feedback no error
33033	Feedback machine / human error
33035	Appearance of feedback (color-frame)
33036	Cursor back at screen center
33037	End of trial

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