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Affect-driven Robot Behavior Learning System using EEG Signals for Less Negative Feelings and More Positive Outcomes

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***Abstract*— Learning from human feedback using event-related electroencephalography (EEG) signals has attracted extensive attention recently owing to their intuitive communication ability by decoding user intentions. However, this approach requires users to perform specified tasks and their success or failure. In addition, the amount of attention needed for decision-making increases with the task difficulty, decreasing human feedback quality over time because of fatigue. Consequently, this can reduce the interaction quality and can even cause interaction breakdowns. To overcome these limitations and enable the interaction of robots with higher complexity tasks, we propose a closed-loop control system that learns affective responses to robot behaviors and provides natural feedback to optimize robot parameters for smoothing the next action. Experimental results demonstrate our affect-driven closed-loop control system yielded better affective outcomes and task performance than an open-loop system with correlated neuroscientific characteristics of EEG signals, thus enhancing the quality of human-robot interaction.**

I. INTRODUCTION

Physiological responses are widely used for effective human feedback to develop closed-loop systems, thereby increasing the ability of human-robot communication. Owing to recent advances in various physiological sensor technologies, closed-loop systems have increasingly carried out practical collaboration between humans and robots, thus augmenting each intelligence [1]–[5]. Recently, electroencephalography (EEG)-based approaches have been proposed to develop human-robot collaboration systems [6], [7] as an alternative. The exceptional advantage of EEG leans on its high temporal resolution enables to study of neurophysiological phenomena in cognitive processes. Event-related potential (ERP) and error-related potential (ErrP) are widely used signals to achieve this, which could enable communication via a signal occurring naturally in the brain while interacting with or observing a collaborating robot. This evoked response in EEG has been widely used as a feedback mechanism to confirm the correctness of their responses.

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However, to provide physiological feedback for evaluating the tasks, this approach requires an end-user to be always attentive while interacting with a robot. In addition, the amount of attention needed for decision-making increases with task difficulty, thereby decreasing human feedback quality over time because of fatigue. Furthermore, most EEG-based task paradigms are cue-based tasks defined by discrete trials, which provide robust test beds for new intuitive decoding algorithms. However, they do not account for the randomness invariably occurring in daily life. In real-world scenarios, communication must be unobtrusive [8]. Otherwise, the robot systems may lose their ability to justify their decisions or actions, resulting in a loss of user trust.

To overcome this limitation, we focused on investigating an affective process of a symbiotic relationship. By hypothesis, a successful closed-loop system should enable users to develop appropriate trust toward the robot system [9], by which they can subsequently increase their understanding and reduce negative feelings toward their perception of machine behavior. In turn, the robot reflects affective feedback by changing how it makes decisions regarding the next action for producing positive outcomes. Motivated by our previous work [10], this study aims to develop a closed-loop control system that learns emotional reactions to robot behaviors and provides affective feedback to optimize their parameters for smooth actions. The degree of valenced negative and positive elicited emotions when the robot approaches the user with objects is learned by the proposed feedback system, enabling users to understand, appropriately trust, and effectively manage the system by comprehending the rationale behind the closed-loop system decisions. Further, we consider how user feedback of emotion can impact the user's affective processes in the brain associated with robot behaviors.

A. Problem Statement

Suppose a robot performs a set of tasks t in which the robot grasps $m \in M$ objects $R(m) = (\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_t)$ and provides them to an end user along with a sequence of velocities $S(m) = (\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_t)$. In a closed-loop system, each user provides an emotional response $Z(m) = (\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_t)$ as a feedback for the robot behavior. A successful cyclic relationship should lead to end-users deepening their understanding of the robot actions with positive feelings and improve its performance with a fast task completion time $C(m) = (\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_t)$. Hence, we can measure the quality of collaboration (ξ) in a closed-loop system simply as

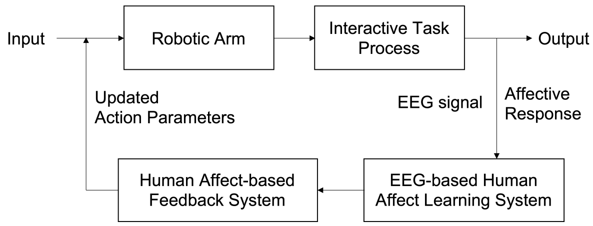


Fig. 1: Overview of the proposed closed-loop affective system.

$$\xi(m) = \sum_{i=1}^{t} (f_C(\mathbf{c}_i) + f_Z(\mathbf{z}_i)), \quad (1)$$

where f_C and f_Z are a family of linear functions balancing the two summation terms. For simplicity, we omit t in the following sections. $\mathbf{z} \in \mathbb{R}^+$ and $\mathbf{c} \in \mathbb{Z}^+$ range from negative to positive feelings and from slow to fast velocities in the increasing order, respectively. Hence, the improved symbiotic relationship in the measurement ξ should lead to reduced negative feelings and increased robot performance by increasing $\mathbf{z}$ and reducing $\mathbf{c}$, respectively.

We should note that human-robot interaction naturally involves an open-loop affective system in an iterative collaborative process where people can preserve lessons and situational information from previous emotional experiences. Hence, considering the quality of collaboration (ξ), we aim to investigate the effectiveness of human affect as a feedback element in a *closed*-loop affective system and compare it to an *open*-loop affective system. We conducted an empirical study for monitoring and learning an end-user's affective process through EEG signals while interacting with a robotic arm.

II. Experimental Methodology

Fig. 1 shows the overview of the proposed system, which consists of three major subsystems each associated with training, evaluation, and test procedures.

A. Participants

We recruited 24 male participants between the ages of 21 and 39 years (mean = 27.4, std = 5.32) for the study and provided an incentive of $10 to each participant. Two groups containing half of the participants each were randomly formed. The participants in the *closed*-loop group provided affective responses $\mathbf{z} \in \{z_{\text{catching}}, z_{\text{giving}}\}$ to the robot behavior $\mathbf{r}$. After a tutorial in a lab setting, the participants were required to conduct a sequence of training, evaluation, and test procedures. The training procedure was carried out in a monitor-based environment where a monitor was placed on a table and positioned approximately 50 cm from each participant. On the contrary, evaluation and test procedures were carried out in a robot-based environment where a robot was placed on a table and positioned at the maximum arm length (= 60 cm) from the participant. This procedure was approved by the Institutional Review Board (IRB) of Human Subjects Research. All studies were performed in accordance with relevant guidelines and regulations. Informed consent was obtained from all participants.

B. Robot Arm Control System

We used an IRB 14000 Yumi robot manufactured by ABB. It was a 2-arm robot with 7-degree of freedom on each arm[1]. Each arm has a gripper on its end to grasp the desired objects and deliver it to a human. The gripper was connected to the main controller for signal and feedback transmission. The variable parameters of the robot system to adjust its motion are the robot arm velocity, acceleration, maximum area for robot arms to move, and postures to grasp and deliver objects to an end-user. In our work, the arm velocity was changed or maintained constant after receiving feedback from the main controller, which could choose the next appropriate movement after analyzing human affective responses.

C. EEG-based Human Affect Learning System

1) EEG Setup and Preprocessing: We recorded EEG signals using a Brain Products system[2] in a laboratory environment. These signals were recorded at a sampling rate of 500 Hz on 32 active AgCl electrodes placed according to the international 10-20 system. The EEG data were downsampled to 250 Hz, common average referenced, and high-pass filtered with a 2 Hz cutoff frequency.

2) Training Procedure: We collected EEG signals associated with affective labels in terms of valence ratings using the international affective picture system (IAPS) [11] having 956 color photographs ranging from everyday objects and scenes. The IAPS dataset aims to provide a standardized set of pictures for studying human affect. Affective responses against all images were rated from 1-9 in terms of valence, arousal, and dominance. Later, we re-scaled the IAPS ratings from 1 to 6 because 1) the emotional response to robot behaviors is simpler to process than pictures from everyday objects and scenes, and 2) the distribution of IAPS ratings is unbalanced. The rationale behind the IAPS usage for training is to secure several EEG samples associated with affective labels, thus preventing users from constructing affective experiences against the robot before the main experiment.

Our training procedure started with a 1-sec baseline session, displaying a fixation cross to collect each participant's neutral baseline. The participants sat at a desk, on which a monitor was positioned 50 cm from them. Then, they completed a set of 30 trials in which five pictures per rounded off label were randomly selected[3]. In each trial, the participants were made to see only a visual stimulus extracted from the IAPS for 3 s without rating their feelings. After removing eye artifacts using independent component analysis with two manually selected components, the 3-second EEG signals were augmented by separating them into two 2-second EEG segments with 1-second sliding windows in

[1]For controlling, ROS source codes developed by KTH RPL were used (https://github.com/kth-ros-pkg/abb)

[2]https://www.brainproducts.com

[3]Video link: https://www.bhyung.me/files/training.html

the time domain. While the IAPS contains various images stimulating human affect rated from negative to positive, the valence ratings cannot be directly applied to build a robust subject-wise classifier owing to inter-subject variability. To overcome this limitation, we first group the segments of the EEG signals into two affective states:

$$\mathcal{P} = \{\forall \mathbf{x}_i | \lfloor y_i \rfloor > y_{th}\}, \mathcal{N} = \{\forall \mathbf{x}_i | \lfloor y_i \rfloor < y_{th}\}, \quad (2)$$

where $\mathbf{x}_i \in \mathbb{R}^{N_c \times N_s}$ indicates the i-th EEG multivariate time-series signals ($\mathbf{x}_i > 0$) and N_c and N_s are the number of channels (= 32) and samples (= 500), respectively. y_i is the valence rating associated with $\mathbf{x}_i$. $\mathcal{P}$ and $\mathcal{N}$ represent the positive and negative affective states divided by the threshold $y_{th} = 3.5$, respectively.

3) Valence Estimation: We used a geodesic distance-based regression to estimate a continuous scale of valence ratings. Owing to the continuity from negative to positive valence, measuring the semantic distance between a query sample and the two sets is reasonable. A query associated with a positive valence should be located outside the boundary of the negative valence set. Furthermore, the positivity increases farther from the opposite boundary. Hence, we first compute the mean of the two sets $\mathcal{P}$ and $\mathcal{N}$ on Riemannian geometry, which is shown to be a promising solution for learning EEG signals within their structured 2D feature representation [12], [13].

$$\bar{\Sigma}_{\mathcal{S}} = \underset{\mathbf{\Sigma} \in \Sigma(\mathcal{S})}{\arg\min} \sum_{i=1}^{N_{\mathcal{S}}} \delta_R^2(\mathbf{\Sigma}, \Sigma(\mathbf{x}_i)), \quad (3)$$

where $\mathcal{S} \in \{\mathcal{P}, \mathcal{N}\}$. $\delta_R(\cdot,\cdot)$ is the Riemannian distance measured by the affine-invariant Riemannian metric (AIRM) [12]. The i-th EEG signal $\mathbf{x}_i$ is represented by a channel $\times$ channel covariance matrix $\Sigma(\mathbf{x}_i)$, estimated using second-order statistics with a shrinkage estimator [14]. More details on Riemannian geometry refer to this study [13].

Given the two Riemannian mean matrices $\bar{\Sigma}_{\mathcal{P}}$ and $\bar{\Sigma}_{\mathcal{N}}$, we assign a query $\Sigma(\mathbf{x}_i)$ to one of the two affective sets $\mathcal{P}$ and $\mathcal{N}$, where the distance is minimized. Denoting the mean matrix selected by the minimized distance as Σ_{min} and its label as y_{min}, the confidence-based similarity between the query and two means is computed for confirming the degree of continuous valence as follows:

$$\begin{aligned}
\Sigma_{\text{min}} &= \underset{\mathbf{\Sigma} \in \{\bar{\Sigma}_{\mathcal{P}}, \bar{\Sigma}_{\mathcal{N}}\}}{\arg\min} \delta_R^2(\mathbf{\Sigma}, \Sigma(\mathbf{x}_i)), \\
d_{\{\text{min, max}\}}(\mathbf{x}_i) &= \delta_R^2(\Sigma_{\{\text{min, max}\}}, \Sigma(\mathbf{x}_i)), \\
\mathbf{z}_i &= y_{\text{th}} + T * (1 - \frac{\exp(d_{\text{min}}(\mathbf{x}_i))}{\exp(d_{\text{max}}(\mathbf{x}_i))}), \quad (4)
\end{aligned}$$

where Σ_{max} is the opposite valence set of Σ_{min}. $\mathbf{z}_i$ increases the polarity of the valence by computing the relative distance between d_{min} and d_{max}. T is the temperature scaling to make $\mathbf{z}$ range from 1-6. In our work, $T = -2.5$ if $\Sigma_{\text{min}} \in \mathcal{N}$; otherwise, $T = 2.5$. The parameter was set through a five-fold cross-validation scheme between the self-assessment and the predicted valence values.

4) Evaluation Procedure: Participants were asked about their feelings regarding robot behaviors, randomly chosen to evaluate the proposed EEG-based human affect learning system. The participants completed a set of 10 trials, in which they were asked to observe the robot positioned at the robot arm maximum length (60 cm) from their eyes, while sitting at a desk without any body movement. At the end of each robot behavior, a beep sound notifies participants to perform a self-assessment of their level of affective scores from 1–6 in terms of valence, which were displayed in the middle of a tablet screen. When participants indicated their self-assessment level by pressing a digit on the screen, they were required to hit a blue button to proceed to the next trial[4]. We recorded EEG signals between the robot initial movement and beep sound notification. The time-variant EEG signals were extracted continuously into 2-second segments. The EEG signals obtained 2 s before the initial movement of the robot were used as a baseline to correct for unrelated variations [15].

D. Human Affect-based Feedback System

The underlying model architecture, which uses a user's affect dynamics to estimate his/ her emotional reaction to robot behavior, was developed to improve the affective transparency in a closed-loop robot system. The emotional feedback $\mathbf{z}_i$ against the current robot behavior causes a change in the next behavior of the robot with the newly computed states $\mathbf{s}_{i+1}$. This change is computed using the following equation:

$$\mathbf{s}_{i+1} = 150 \cdot f(\mathbf{z}_i) + \mathbf{s}_i, \quad (5)$$

where $f(\cdot)$ a family of linear functions. In our study, we use

$$f(\mathbf{z}_i) = \text{sgn}(\mathbf{z}_i - y_{\text{th}}) \frac{1}{\ln y_{\text{th}}} \ln |\mathbf{z}_i - y_{\text{th}} + 1|, \quad (6)$$

where $\text{sgn}(\mathbf{z}_i - y_{\text{th}})$ is the sign function, which returns -1 if $\mathbf{z}_i < y_{\text{th}}$. A robot increases $\mathbf{s}_{i+1}$ smoothly in the next trial when a user feels positively ($\mathbf{z}_i > y_{\text{th}} = 3.5$) against the current robot behavior in trial i.

1) Testing Procedure: Experimental Paradigm: The objective of the experiment is to realize affective transparency in a closed-loop system for human-robot interaction, which examines whether internal decisions of the robot regulated by affective feedback not only yield positive outcomes but also reduce negative feelings toward the robot so that the quality of human-robot interaction is improved by fostering trust. To explore the feasibility of EEG-based human affect for robotic tasks in a closed-loop manner, a paradigm of the feedback system was designed to allow users to interact with a robot. Fig. 2 shows the training, evaluation, and testing procedures, where the human observes the robot and influences its behavior using natural feeling patterns. As a robot comes closer to a human, the potential risk of inter-collision increases. This may decrease valence, which leads to negative feelings, such as fear, of the end-user.

[4]Video link: https://www.bhyung.me/files/evaluation.html

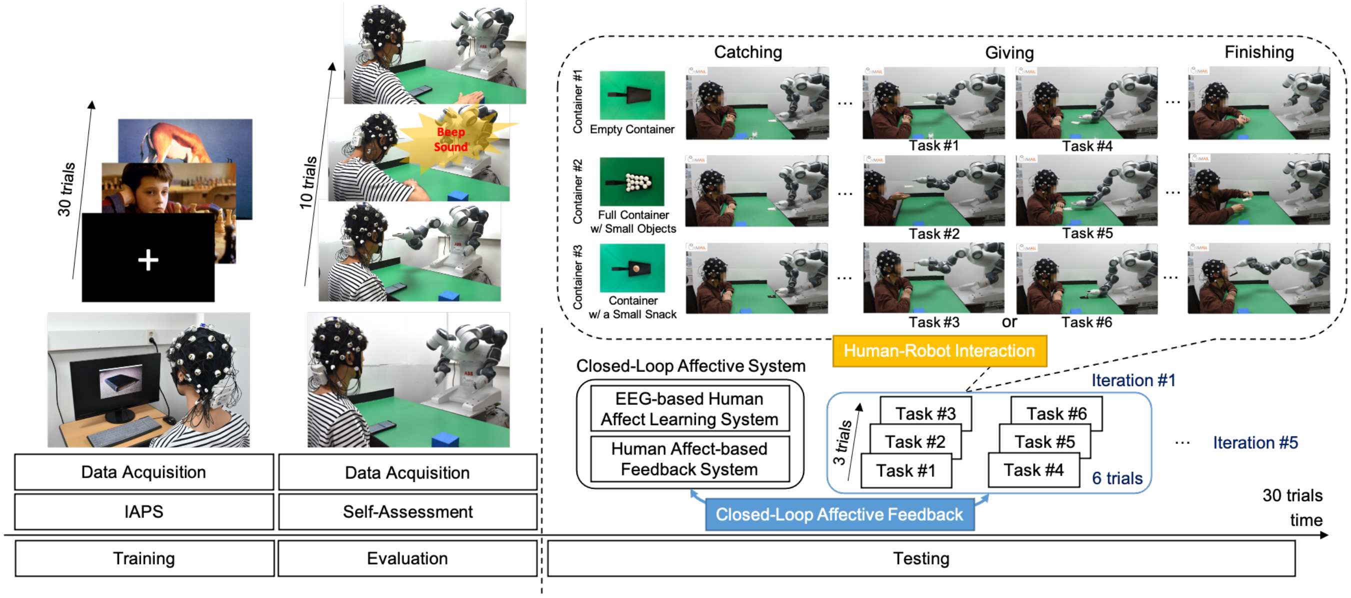


Fig. 2: Experimental Paradigm. After training and evaluation procedures, all participants conduct six tasks which consists of "catching", "giving", and "finishing" stages with different levels of robot approaches during five iterative times (= a set of 30 iterative trials) in terms of the task completeness time and valence. Each interactive trial starts and ends by pushing the blue button.

The paradigm aims to study 1) the emotional difference with different levels of robot approaches and 2) effect of affective feedback in a closed-loop system on the different levels of approaches during iterative tasks in terms of the task completeness time and valence.

Similar to the evaluation procedure, the robot was placed on a table positioned approximately 60 cm from the participants sitting at the table. The blue button is also located right down on the table to avoid any collision with the robot behaviors. The participants were required to conduct a sequence of interactive trials with the following three tasks:

1) Task 1: The robot grasps *the empty container* and provides it to the participant. Then, the participant was required to *fill the container with small objects*, which were filled in a bottle. The task is completed when they hit the blue button after placing all objects in the container.
2) Task 2: The robot grasps *the full container with small objects* and provides it to the participant. Then, the participant was required to *empty the container* by pouring the objects into an empty bottle. The task is finished when they hit the blue button after emptying the container.
3) Task 3: The robot grasps *the container with a small snack* and provides the same to the participant. Then, the task was finished when the participant successfully *caught the food with their mouth* with a hit on the button.

Each of the three tasks consists of "catching" and "giving" a container ($\mathbf{r} \in \{r_{\text{catching}}, r_{\text{giving}}\}$) and "finishing" the task to study the emotional difference with different levels of robot approaches and effect of affective feedback. In each "catching" stage, the robot catches the container placed on the middle of the table. Then, in each "giving" stage, the robot gives the container either 1) close to the user at the face level or 2) on the desk in front of him. Hence, all participants conducted six trials to finish the three tasks iteratively[5]. They were required to iterate five times, that is, a set of 30 interactive trials as fast as possible without dropping any of the objects. Each interactive trial starts and ends by pushing the blue button. In between iterations, the participants could have a small break, if necessary. EEG signals of various lengths during the two stages were extracted continuously into 2-second segments as inputs for estimating valence. The EEG signals recorded 2 s before the initial movement of the robot were used as a baseline to correct unrelated variations [15]. As described in [16], the current emotional outcome may guide the next behavior. Hence, affective residues from the current trial could have some effects on the subsequent trials in both groups. However, in this study, we aim to focus on how such an affective residue can be used in a robotic system to accelerate task completeness performance.

We measured the task completion time unless any of the small objects or snacks were dropped under the table. The tasks with containers #2 and #3 were designed to have unreliable velocities. If the velocity value s is too fast, the object was easily dropped from containers, so more time was required to finish their goals, such as eating and emptying. The initial velocity is set to 500, which the three experienced users who are not involved in either the closed

[5]Video link: https://www.bhyung.me/files/testing.html

TABLE I: Correlates of affective response and the completed time. Only significant correlations were reported ($p < 0.001$).

	Open-loop		Closed-loop	
	Catching	Giving	Catching	Giving
Container #1	-0.14	-0.19	-0.2	-0.26
Container #2				-0.55
Container #3			-0.63	-0.72

TABLE II: Electrodes for which EEG signal was significantly correlated with valence ($p < 0.01$). Mean of the subject-wise correlations (R), the most negative (R-), and the most positive correlation (R+).

θ				α			
Elec	R	R-	R+	Elec	R	R-	R+
O1	0.08	-0.11	0.35	P7	0.14	-0.19	0.35
P7	0.07	-0.33	0.39	O1	0.07	-0.14	0.22
				O2	0.05	-0.24	0.42

β				γ			
Elec	R	R-	R+	Elec	R	R-	R+
FC5	0.08	-0.51	0.38	O1	0.06	-0.24	0.45
F3	0.07	-0.40	0.28	Fp1	0.11	-0.24	0.32
O2	0.05	-0.24	0.33	Fp2	0.04	-0.32	0.44
Oz	0.09	-0.33	0.49				
FC2	-0.06	-0.41	0.22				

or open loop groups agree. The participants in the *closed*-loop group provided affective responses $\mathbf{z} \in \{z_{\text{catching}}, z_{\text{giving}}\}$ to the robot behavior $\mathbf{r}$. Based on the affective feedback, the closed-loop system computes the velocity configuration $\mathbf{s} \in \{s_{\text{catching}}, s_{\text{giving}}\}$ for the next robot behavior. On the contrary, the participants in the *open*-loop group were not allowed to provide any affective feedback; the robot maintained the same configuration during the experiments.

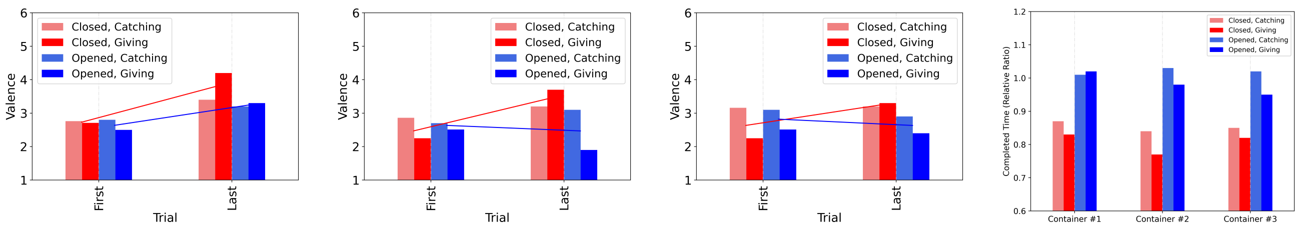
III. Result and Discussion

Fig. 3 shows the valence values and the completed times throughout the experiment for the two groups, respectively. Both groups of participants reduced the task completeness time and increased valence while carrying out tasks with container #1. This suggests that anticipating the next behavior of the robot can help the participants learn a lesson and leave a strong affective cue that may guide future behavior for a simple task. Thanks to training and practicing from consecutive trials, people chose a different course of action for completing some tasks (i.e., the container #1) faster than before with better emotional outcomes. This also implies that the participants develop their understanding through memory retention and recall processes about its reasoning through consecutive and repeated trials.

Affective residues further facilitated interaction when they were used as feedback elements. We observed the *closed*-loop mechanism exhibited greater improvements in completed time and valence than the *open*-loop system. Changes in the scores (the last–first trial) of both values for the *closed*-loop group were greater than those for the other group. From the fact that the giving stages are designed to have unreliable velocities of the robot arm and require closer approaches than the catching stage, the participants in the *closed*-loop group were more likely to correctly and confidently agree with the robot behaviors of grasping and giving objects. These results imply that participants perceived using the *closed*-loop affective system to be more productive (=faster completed time) and comfortable (=less negative feeling) than using the *open*-loop affective system when performing the iterative tasks.

We analyzed the Spearman's rank correlations ($p < 0.001$) between the completed times $\mathbf{c}$ and valence values $\mathbf{z}$, which suggests a highly negative correlation in the *closed*-loop group, as reported in Table I. In addition, we observed that the giving stage exhibits a stronger relationship than catching. Because the giving stage requires a robot to approach a user closer, the statistical relationships between the two objects implies that increased valence improves the overall performance when their tasks require mutual approaches in interaction. When the participants in the *closed*-loop group felt negativity due to the personal affective experience or the interactive outcomes (i.e., mistakes) against the robot approach behaviors during the initial trials, the robot reduced its velocity properly following the proposed feedback system. Inversely, the robot velocity in the closed-loop system increased when the participants felt positive toward the approaches. This strategy contributes to improve the intimacy between the two objects, not only increasing the number of successes during the interactive trials but also decreasing negative feelings. For instance, we observed that giving small objects and snacking on containers #2 and #3 enabled users to empty the container and eat the snack successfully. This consecutive success further led to a reduction in task completion times. It should be noted that the participants in the *open*-loop group could also reduce the completed task times owing to training and practicing from consecutive trials, as shown in Fig. 3d. However, they failed to show any statistical relationships between interactive trials (Fig. 3d) and correlation between valence and task completion times (Table I). Hence, one side change in the *open*-loop system is insufficient to build a high-quality interaction, which requires appropriate trust between the two objects.

Fig. 3 and Table I indicate that the users elicited various valenced emotions when the robot approached them with three containers. To investigate EEG activities when people have different affective responses using the robot approach, we analyzed the statistical difference of mean changes in the four frequency bands (theta, alpha, beta, and gamma) of the EEG signals. Between the four frequency bands and valence ratings, we computed the p-values of the Spearman for the



(a) Container 1 (b) Container 2 (c) Container 3 (d) All Containers

Fig. 3: (a, b, c) Comparative results of the the averaged valence values between the two groups (Red - the *closed*-loop affective group, Blue - the *open*-loop affective group). End-users of the *closed*-loop affective group finished the interactive tasks while eliciting less negative feelings. (d) The averaged ratios of task completed time at the last to the first trial between the two groups.

left- (positive) and right-tailed (negative) correlation tests for all participants in the *closed*-loop group. Then, we combined them into one p-value using Fisher's method [17]. The resulting p-values for the correlation directions, electrodes, and frequency bands are reported in Table II. The frequency in the frontal and occipital cortices such as FC5, FC2, F3, O1, and O2 was significantly correlated with valence when the robot approached participants. We also found that EEG powers in the alpha and beta bands over the cortices were significantly different against the baseline emotion when the users felt strongly positive ($\mathbf{z} > 4$) and negative valence ($\mathbf{z} < 3$) response to the robot approach. The discovered activation supports neuroscientific studies on emotional progress with visual processing [18]. EEG activation between the frontal and occipital regions was also reported to be related to positive and fear emotions [19].

IV. Conclusion

We demonstrated that our closed-loop affective system yielded better affective outcomes and task performance. The robot could improve its choice of subsequent behavior as they received a user's affective responses as feedback elements and provided actions on those decisions to the user. We also analyzed the neuroscientific characteristics of EEG signals when taking objects toward users in human-robot interaction. In future, we will develop an EEG-based computational model to capture social signals behind the human-robot interaction. Particular geometry such as Riemannian manifolds will be exploited to build reliable automated systems, which are expected to accelerate the usability evaluation process in real-world robotic applications.

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