Unification of Neural Systems between Human and Humanoid Robot

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***Abstract*—This paper describes a novel cognitive neurobotics approach that makes it possible for a humanoid robot to perform one of several behaviors by reading the intentions of the user via brain signals. The biological neural system of a human generates brain signals during cognitive processes. An artificial neural system, part of our BCI system, translates the brain signal into the intentions of the user. Another artificial neural system of a humanoid robot controls its behavior based on visual perception and the user's intention. Furthermore, we designed a robotic experiment to investigate our approach. Experimental results demonstrate that the unification of neural systems enables the robot to connect with the biological neural system of a user.**

I. Introduction

"How does a human think?" is one of the oldest and greatest unsolved questions from the dawn of history to the present day. To answer this question, Plato, an Ancient Greek philosopher, founded epistemology – a field of philosophy about the nature, origin, and limits of knowledge. Plato and his followers believed that our minds and souls are in the heart. In modern times, we discovered that the nature of the mind is derived from electrochemical activities between the physical brain and nervous system. The endeavor to understand the nature of the mind is led from epistemology to cognitive science which is a multidisciplinary study that researches the cognitive processes of both humans and animals.

Cognitive robotics is an approach to investigate human cognitive processes and adapt them to achieve cognitive behaviors and intelligence in robots. The primary goal of a cognitive robot is to act and react appropriately in real physical environments much like a human. Teaching the motion of robot from multiple demonstrations, also referred to as tutoring or learning by imitation is a good example of cognitive robotics. Like human and ape infants imitate and learn behaviors from their parents [1], [2], many studies show that imitation is also a useful and convenient method to teach new behavioral skills to robots [3]–[6]. The robot monitors the behavior of other agents through visual perception or posture recording of motors and then the robot tries to replicate that behavior using dynamic model such as a Gaussian mixture model (GMM).

Another approach to understand the human mind through robotics is neurobotics. Neurobotics is more directly combined with neuroscience rather than cognitive science. It focuses more on the computational model of the brain and neural-inspired artificial agents rather than cognitive processes. A neurobot usually has a non-linear dynamic model as a control system based on bio-inspired computational models such as dynamic artificial neural networks [7]–[10]. An advantage of using them is that it can be a distributed representation. For example, motion planning based on GMM have to switch models to teach different behavior patterns. However, neural network can learn multiple behaviors in a single model. Additionally, some of these studies are also meaningful for cognitive robotics and human-robot interaction. Ito and Tani suggested a variant of a recurrent neural network based on a mirror neuron model for imitative interactions of a humanoid robot [9]. Sugita and Tani demonstrated binding between linguistics and behavior of a mobile robot using the same model [11].

From the perspective of human-robot interaction and neuroscience, brain-computer interface (BCI), which is an interactive technology that measures and translates the brain activity to control the external device [12], is also an interesting approach. Controlling mobile robots and humanoid robots is one of the most popular applications of BCI because it provides a more intuitive, natural and telepresent control. It is usually used to navigate a robot [13], to target objects [14], or even both [15].

Extending these lines of work, we presents a novel cognitive neurobotics approach that makes it possible for a humanoid robot to perform one of several behaviors according to a user's intentions, directly read from the brain signals.This was achieved by a unification of three different neural systems: the biological neural system of the human, which generates the brain signals during cognitive process; an artificial neural system of the BCI system, which translates the brain signal into the intention of the user; and an artificial neural system of a humanoid robot, which controls its behavior according to the current sensorimotor state and the translated intentions of user.

II. Robot Experiment

We designed a robotic experiment to investigate the feasibility of our approach. Our experiment enables the robot to learn and regenerate multiple behaviors by recognizing the intention of the user. The experiment consisted of simple interaction tasks. The humanoid robot tries to touch one of two boxes with its right arm. Green and blue boxes were placed on two fixed and reachable positions in front of the robot. The robot could percept the position of each box through an eye camera. The robot learned these sequences of behaviors and perceptions from demonstrated movement pattern by a user. And then, it performed tasks corresponding the intention of user which recognized by the BCI system.

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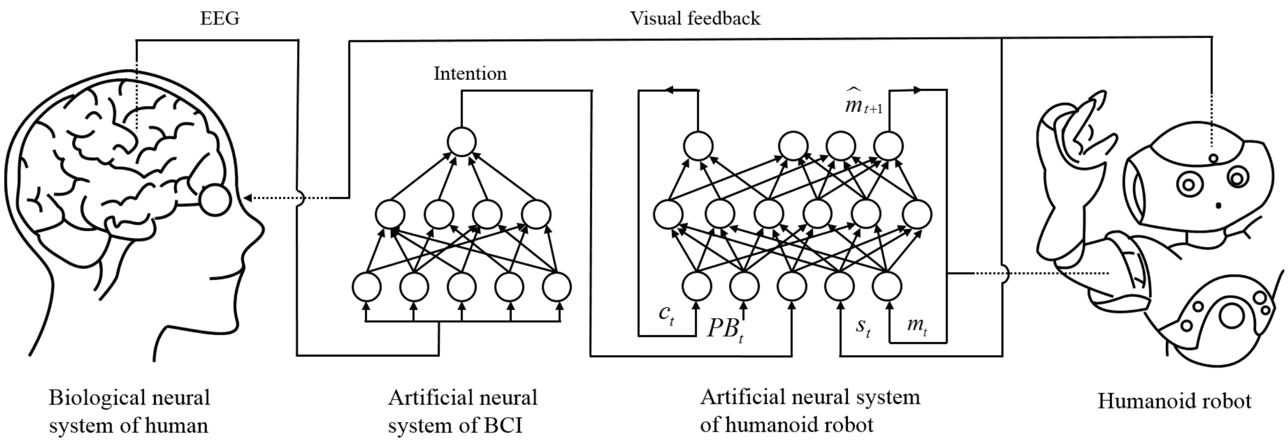


Fig. 1. Schematic diagram of the unification of neural systems between a human and humanoid robot.

III. Model

A. Unification of Neural Systems

Our approach is based on the unification of three different neural systems. First, the brain of a user, the biological neural system of a human, produces brain signals as a result of the cognitive processes of selecting a box which the robot should touch. Second, electroencephalography (EEG) signals involving the intention of user flow into an artificial neural system of the BCI system which extracts and translates brain signals into the user's intentions for the robot. Finally, an artificial neural system of the humanoid robot controls its own the dynamic motor system based on the its current sensorimotor state and recognized intention of the user. Fig. 1. illustrates the schematic diagram of the unification of neural systems between a human and humanoid robot.

B. Biological Neural System of a Human

We used the oddball paradigm of P300 event-related potentials to evoke intentions of which target objects were desired by user. P300 potential is an approximately 300 ms delayed event related potential to visual or auditory stimulus through the process of decision making. It is usually elicited by sequences of repetitive audio or visual stimuli including frequent non-target and infrequent target stimuli. Whenever a subject counts the number of target stimuli, event related potentials are detected across the parieto-central area of the scalp after approximately 300 ms in EEG signals. To scan intentions of a user from the biological neural system of a user, the robot displayed a forwrd-facing camera view on a monitor and provided visual stimuli to evoke P300 potentials. Each epoch of the brain signals were recorded using an EEG acquisition device after the stimulus onset.

C. Artificial Neural System of the BCI system

Acquired brain signals were translated by an artificial neural system of the BCI system. We used a discrete wavelet transform (DWT) to enhance the signal-to-noise ratio of evoked potentials and reduce the dimension. The wavelet transform is one of the most popular approaches of obtaining a time-frequency representation to overcomes the disadvantage of the Fourier transform, which can only represent signals in the frequency domain, not the time domain [16]. DWT is also a conventional feature extraction method of P300 potentials [17]–[19]. The sub-band coding property of DWT plays a critical role in the denoising and dimensionality reduction processes of P300-based BCI. It divides a brain signal into two time-frequency representation; approximation and detail coefficients which contain the lower and upper half of collected frequencies, respectively. Each coefficient is subsampled by two.

The approximation coefficients of the brain signal capture the dominant features of P300 evoked potentials: the slow wave. Then, these wavelet features are identified by the artificial neural system of the BCI system, a simple two layer feedforward neural network into either a P300 potential or not.

D. Artificial Neural System of a Humanoid Robot

An artificial neural system, the dynamic control system of a humanoid robot, generates sequences of motion based on the position of boxes and the translated intentions of the user. For the artificial neural system of the humanoid robot, we applied a recurrent neural network with parametric bias (RNNPB) which can learn, regenerate, and recognize multiple sequences of data [9]. It is a non-linear dynamic system inspired from the mirror neurons of the brain which suggests that both recognition and generation of behaviors are processed in the same neurons. RNNPB is a variant of a Jordan-type recurrent neural network with an additional layer called the parametric bias (PB) layer corresponding to the mirror neurons. They are bifurcation parameters that can ideally encode and identify an infinite number of dynamic patterns.

The operation of a RNNPB is divided into three categories; learning, generation, and recognition. In the learning phase of the RNNPB, the model searches for not only optimal synaptic weights for the training sequence patterns, but also a series of optimal PB vectors which are specific to each training sequence. Synaptic weights and PB values are updated iteratively for each training pattern using a back-propagation through time algorithm [20]. The PB values of L steps of the forward dynamics are back-propagated as follows.

$$\delta\rho_n^i = \sum_{t=0}^{L} \delta_t^{bp^i} \tag{1}$$

$$\Delta\rho_n^i = \epsilon_{pb} \cdot \delta\rho_n^i + \eta_{pb} \cdot \Delta\rho_{n-1}^i \tag{2}$$

$$p_n^i = \sigma(\rho_n^i) \tag{3}$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{4}$$

where ϵ_{pb} is the learning rate and η_{pb} is the momentum for PB nodes. The internal potential values ρ_n^i of i th PB node at training epoch n are calculated from the summation of the delta error $\delta_t^{bp^i}$ of i th PB node for L steps and the last change of i th PB node. The PB value p_n^i of the i th PB node at training epoch n is activated by the logistic sigmoid function σ.

Once the synaptic weights and each PB value for a sequence are determined in the learning operation, the model is able to generate and recognize each of the trained patterns. For closed-loop generation of a specific trained pattern, a PB vector is used which was obtained as a result of learning a sequence. Then, the forward dynamics of RNNPB reproduce a trained pattern according to the PB values without receiving the input externally. RNNPB can recognize one of the trained sequences of data. The recognition of patterns is similar with learning. Updating the PB vector without changing synaptic weights make the PB values converge on the specific values corresponding to a trained pattern.

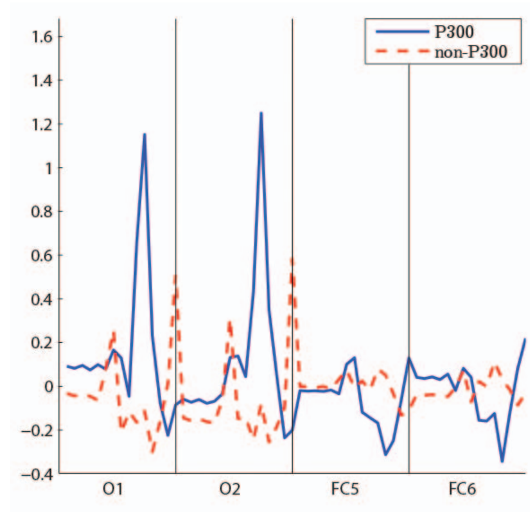
IV. Experimental Result

A. BCI Training

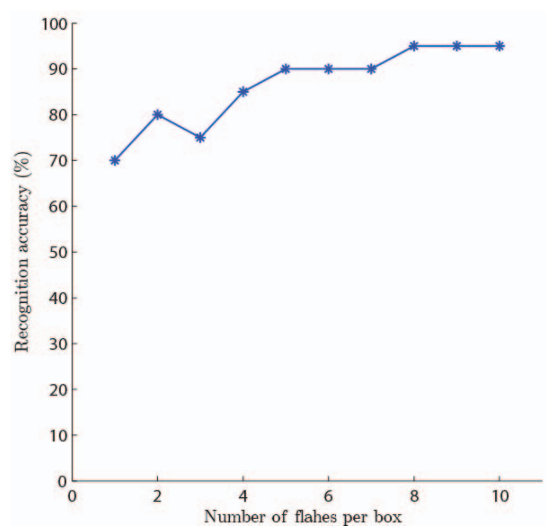
To construct the artificial neural system of the BCI system, a training and testing dataset of EEG was first collected for a subject. The subject sat comfortably in front of a monitor wearing an EEG acquisition device. A forward-facing view from a camera located in eyes of the robot was displayed on a monitor at 10 fps. In each trial, the subject was asked to count the number of flashes for a target box. When a box is flashing, the other box is blacked out in the displayed images. The interstimulus interval is 250 ms. Each box was flashed up to 10 times in a random order. For each flash, an epoch of EEG signals corresponding to the flashing of a particular box was recorded for 600 ms. Each trial was repeated 40 times; 20 trials for training and 20 trials for testing.

In this study, we used an Emotiv EPOC neuroheadset which can record EEG signals at a sampling frequency of 128 Hz from the 14 channels. The BCI system processed the 3-level decomposition of DWT with Duabechies Wavelets order-4 from four channels of EEG signals: O1, O2, FC5 and FC6. Approximation coefficients of level-3 which contain time and frequency representation of EEG at 0-8 Hz were calculated from a 600 ms window after the stimulus onset and were used to train the artificial neural network of the BCI system. A two layer feedforward neural network with logistic sigmoid activation function mapped 60 input features into one output indicating whether there is a P300 potential or not. The hidden layer consisted of ten hidden nodes. It was trained by the scaled conjugate gradient algorithm [21] during 5000 epochs. The mean squared error of the trained network is 0.05.

Fig. 2. illustrates the test results of the P300-based BCI. Fig. 2a. plots wavelet features of P300 and non-P300 potentials averaged across epochs. The continuous line represents the average over target stimuli and the dashed line corresponds to the average over non-target stimuli. Fig. 2b. shows recognition accuracies over the number of flashes per object. These results are comparable to other algorithms in our previous study [15].



(a)



(b)

Fig. 2. Test results of the P300-based BCI. (a) wavelet features of P300 and non-P300 potentials averaged across epochs. (b) recognition accuracies over the number of flashes per object.

B. Training the Humanoid Robot

In this experiment, we used a programmable humanoid robot, Aldebaran Nao [22], to investigate our model. To learn specific behaviors, the robot motors were set to passive mode. In this mode, during kinesthetic teaching trials, the trajectories of the angle values of each joint were recorded at a rate of 5 Hz through motor encoders. Four DOF of the right arm were used in the experiment, and the lower body was set to a constant position, maintaining a stable posture. images from a camera

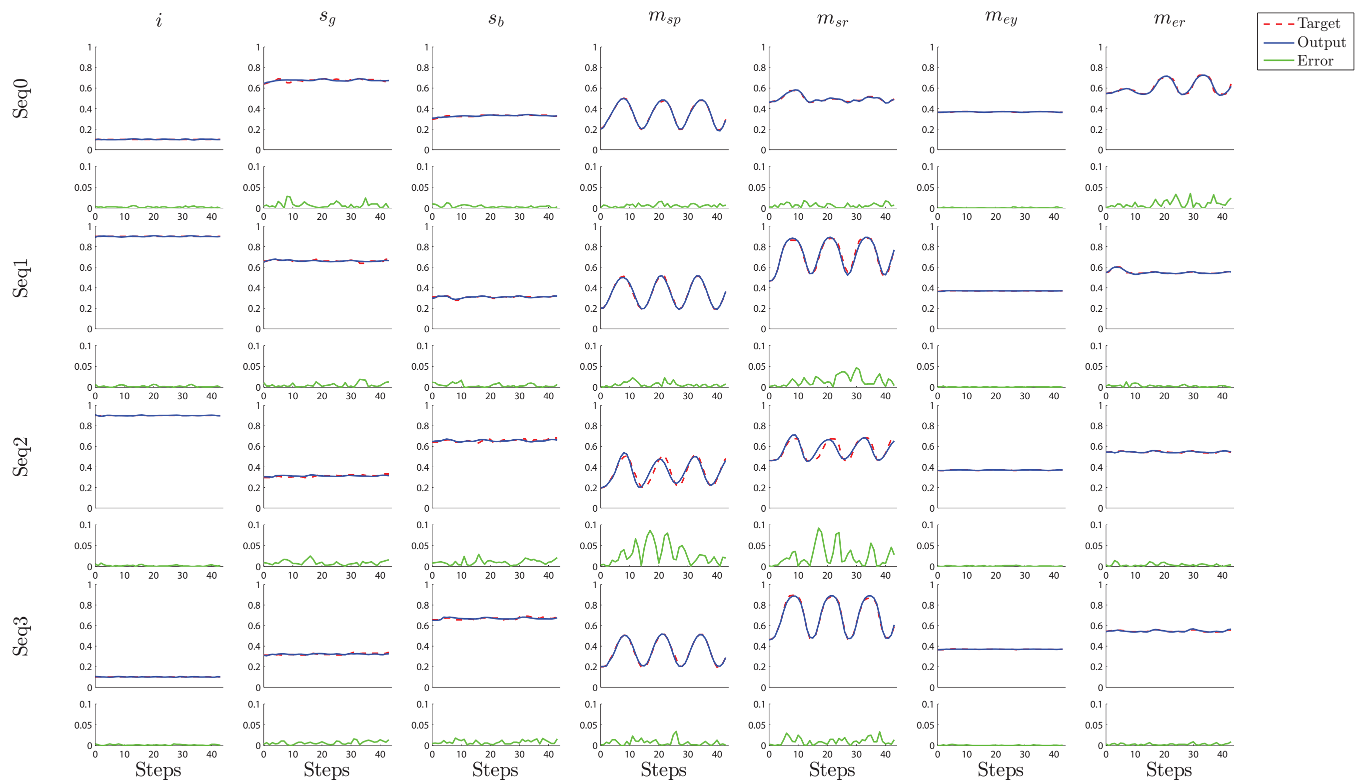


Fig. 3. Training results of RNNPB.

in the eye of Nao were acquired every 100 ms and processed to detect the coordinates of two boxes.

To train the artificial neural network to control the robot, the subject demonstrated four different sequences of sensorimotor state by physically guiding the robot's right arm. This touch-and-retract actions were repeated several times to obtain each training sequence pattern. The first sequence "Seq0" was a series of senorimotor states to touch the green box when the green and blue box were placed on left and right side of the robot respectively. The sequence "Seq1" was touching the blue box in the same position. Then we exchanged the positions of the two boxes and repeated the movement of touching the blue and green box for "Seq2" and "Seq3". Each step of the training sequences contains seven values: one intention, two sensors, and four motor states. The intention i is a binary variable which indicates the translated intention of user (0: "Touch the green box" or 1: "Touch the blue box"). The two sensor values s_g and s_b have the x-coordinate of green and blue box in the robot's view respectively. And the four motor state are the joint angles of right arm: shoulder pitch m_{sp}, shoulder roll m_{sr}, elbow yaw m_{ey}, and elbow roll m_{er}. Theses values were normalized within the range [0.1, 0.9] using the minimum and maximum values of each domain. RNNPB with 30 context nodes, 40 hidden nodes, and 2 PB nodes were trained to recognize and generate the four training sequence patterns during 50000 epochs. The learning rate ϵ_{pb} is 0.05 and the momentum η_{pb} is 0.9. Each training sequence consisted of 45 steps, approximately three cycles of a sensorimotor and intention pattern.

Fig. 3. show the training result of RNNPB. The red dashed line corresponds to the target values of training sequences and the blue solid line represents the predicted values by the trained RNNPB. The green continuous line indicates the absolute error between the target and predicted values. The root mean squared error of RNNPB is less than 0.0004. The PB vectors of "Seq0", "Seq1", "Seq2", "Seq3" are (0.91, 0.94), (0.05, 0.81), (0.11, 0.11), and (0.94, 0.07) respectively.

C. Real-time Experiment

We conducted a real-time interaction experiment through the unification of neural systems between a human and humanoid robot. Each interaction task consisted of two phases: recognition and behavior. In the recognition phase, the robot provides the visual stimuli to read the intention of a subject similar to the BCI training. The visual stimuli were elicited every 250 ms. Five flashes per box were used to evoke the P300 potentials. A recognition phase took a total of 2.5 s. To measure the performance of our approach, the subject was asked to intend to touch a specific box before the start of a recognition phase. After the recognition of the intention, the robot tried to generate the trained sequence of a behavior corresponding the intention of user. In a behavior phase, the forward dynamics of the artificial neural system of the humanoid robot generated 45 steps of motor output based on the current sensorimotor states and the intention. It was approximately three cycles of a touch-and-retract action that touch a target box three time and took 9 s. The PB vectors were updated through the back-propagation of the past 30

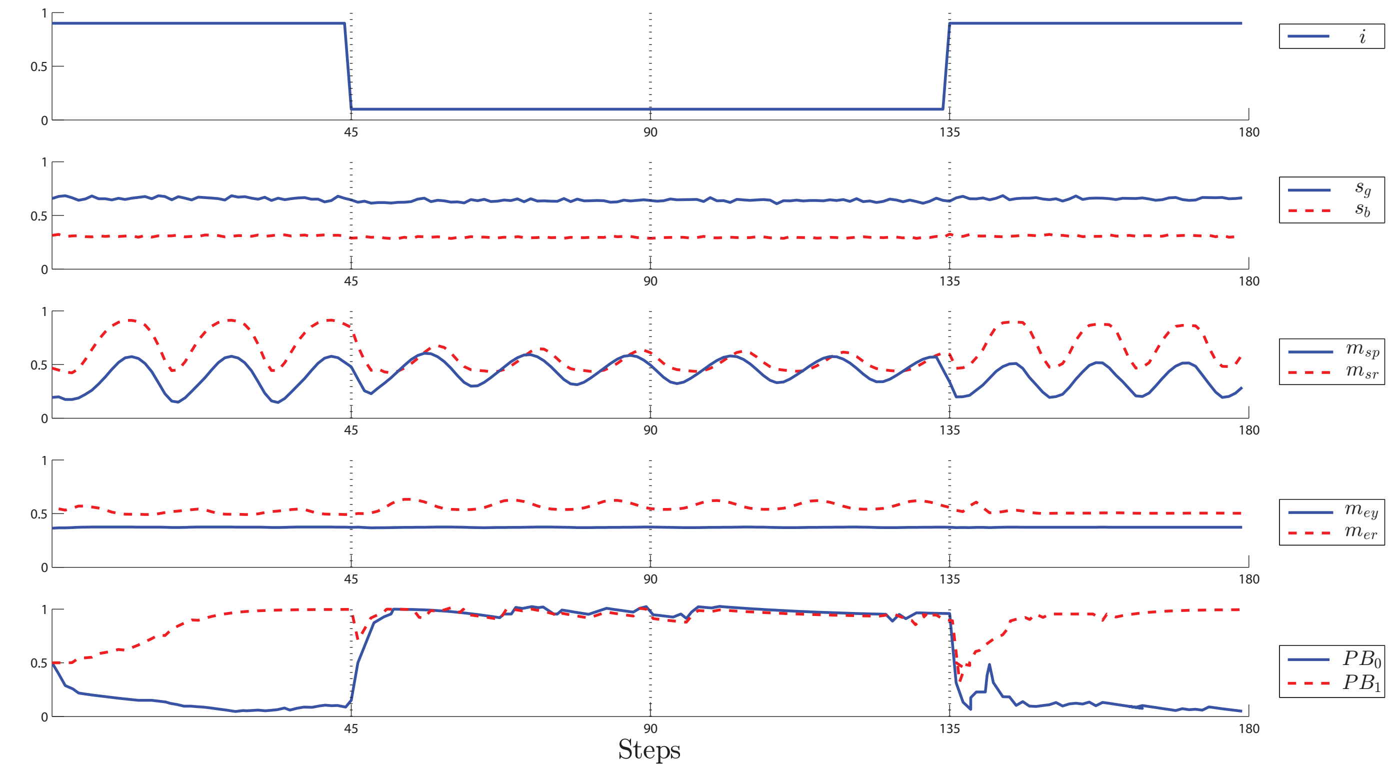


Fig. 4. The sensorimotor states of the robot and the intentions of the user in a session.

steps. The subject performed eight sessions of the experiment. Each session consisted of the four sequential interaction tasks. The positions of two boxes were fixed in a session. To read the intention of the subject for the next interaction task in a session, the recognition phases between interaction tasks were proceeded during the last cycle of the action.

Fig. 4. shows an example of the sensorimotor states of the robot and the intentions of the user in a session. The dotted vertical line indicates the change of the interaction tasks. The artificial neural system of the humanoid robot was succeeded in generating the sequences of behavior according to the user's intentions. The PB vector of the RNNPB converged on the specific values corresponding to recognized patterns. The subject failed three interaction tasks out of the total 36 interaction tasks. They were caused by the misclassification of the intentions in the artificial neural system of the BCI system.

V. Conclusion

This paper proposes a novel cognitive neurobotics approach that makes it possible for a robot to perform one of several learned behaviors according to the intentions of a user, which is directly read from their brain. The intent of user to touch one of two boxes were translated through a P300-based BCI. A non-linear recurrent neural network controls the trajectory of the right arm of a humanoid robot based on the current sensorimotor state and the direction from P300-based BCI. We believe that this paper demonstrates the feasibility of carrying out the unification of neural systems between humans and humanoids robot through a combination of three different neural systems. In future work, we will continue to investigate the more practical and natural unification of neural systems between humans and humanoid robots which can recognize the intention of a user and generate the behavior simultaneously.

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