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A BRAIN COMPUTER INTERFACE BASED HUMANOID ROBOT CONTROL SYSTEM

Wei Li[1], Christian Jaramillo[1], Yunyi Li[2]

[1]Department of Computer and Electrical Engineering and Computer Science
California State University, Bakersfield
9001 Stockdale Hwy, Bakersfield, CA 93311-1022, USA
wli@cs.csubak.edu

[2]Department of Psychology and Neuroscience, Duke University
417 Chapel Drive, Durham, NC 27708-0086, USA
Yunyi.li@duke.edu

ABSTRACT
This paper develops a brain-computer-interface (BCI) based humanoid robot control system. The system consists of an electroencephalograph (EEG), a humanoid robot, and a CCD camera.

The goal of our study is to control humanoid walking behavior through neural signals acquired by the 32 channel EEG. The humanoid robot is equipped with an onboard PC and has 20 degrees of freedom (DOFs). The CCD camera takes video clips of a subject or an instructor hand postures to identify mental activities when the subject is thinking “turning right,” “turning left,” or “walking forward.” The developed control system is a powerful tool to investigate relationships between complex humanoid robot behaviors and human mental activities.

As an example, in this study we implement three types of robot walking behaviors: turning right, turning left and walking forward based on robot kinematics, and perform two sets of experiments on acquiring brainwaves correlated to the mental activities. We propose an approach to extracting the features of brainwaves to control the robot walking behaviors.

KEY WORDS
BCI system, humanoid robot, neural signal processing, mind control, robot walking behavior.

1. Introduction

Brain Computer Interface (BCI) sets up a new communication channel which can be used to identify subjects’ mental activities by analyzing brainwaves [1][2]. BCI systems are classified into invasive and non-invasive: An invasive BCI system uses electrodes implanted over the brain cortex (requiring surgery) to record signals, and a non-invasive BCI system uses an EEG electrode cup to acquire brainwaves from skin surface on a scalp. These BCI systems extract specific features of mental activities and convert them into device control commands.

Figure 1. BCI-based humanoid robot control system

Recently, there has been an increasing interest in BCI applications to control robots through neural signals. The works [3]-[5] propose and review directly employing cortical neurons to control a robotic manipulator. The research groups [6]-[8] report the navigation of mobile robots using BCI, including the control of a wheelchair [9]-[11]. The article [12] presents an example of humanoid robot control through a BCI system.

Comparing with manipulators and mobile robots, humanoid robots are more advanced as they are created to imitate some of the same physical and mental tasks that humans undergo daily [13], but control of humanoid robots is much more complex. Humanoid robots are being developed to perform some complicated tasks like personal assistance, where they should be able to assist the sick and elderly, and dirty or dangerous jobs.

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However, for people with severe motor disabilities it is important to establish augmentative communication with humanoid robots for personal assistance [14].

This paper develops a brain-computer-interface (BCI) based humanoid robot control system, integrating an electroencephalograph (EEG), a humanoid robot, and a CCD camera, as shown in Figure 1. This system can serve as a platform to investigate relationships between complex humanoid robot behaviors and human mental activities and to validate algorithms performance of controlling humanoid walking behaviors through brainwaves.

As an example, in this paper we implement three types of robot walking behaviors: turning right, turning left, and walking forward based on the robot kinematics. Control of the three types of behaviors is provided through three mental activities of turning right, turning left, and walking forward which are correlated with their robot walking behavior counterparts. We conduct two sets of experiments on recording brain signals during mental activities. The first set of experiments records the subject's mental activities when the subject is thinking "turning right," "turning left" and "walking forward." The subject simultaneously moves the right hand, the left hand, and both hands when thinking "turning right," "turning left" and "walking forward." The recorded brainwaves in this experiment may include the muscular signals caused by the subject's hand movements. The second set of experiments records the subject's mental activities which are triggered by an instructor's voice commands. In this set of experiments, the instructor moves the right hand, the left hand, and both hands. We analyze the neural signals correlated to the mental activities and use phase features of delta-band brainwaves to activate the humanoid robot walking behaviors.

This paper is organized in six sections. Section 2 introduces the BCI-based humanoid robot system. Section 3 describes the implementation of humanoid robot walking behaviors. Section 4 discusses how to use brainwaves to control the robot walking behaviors. Section 5 reports our experiment results. Finally, section 6 draws the conclusions on the BCI-based humanoid robot system and proposes our further research.

2. BCI-Based Control System

2.1 Data Acquisition System

The most important part in our BCI interface is a Cerebus™ Data Acquisition System with a 32 microelectrodes cap. The Cerebus™ includes an amplifier, an amplifier power supply, and neural signal processor, as shown in the bottom window of Figure 1. This system is capable of recording from both surface and extracellular microelectrodes, and the system provides several on-line processing options for neural signals including noise cancellation, adjustable digital filters, simultaneous extraction of spike and field potential recordings from microelectrodes, and automatic/manual online spike classification. The BCI interface records the neural signals during mental activities.

2.2 Humanoid Robot

Our system uses a KT-X PC humanoid robot manufactured by Kumotek which has 20 degrees of freedom (DOFs), 12 DOFs located on hips, knees, and ankles, for humanoid robot walking, 6 DOFs on shoulders and arms for arms motion, and 2 DOFs for head yaw and pitch motion. The KT-X PC incorporates a 1.6GHz Atom Z530 processor, memory expansion slots, video input for vision, speakers, a 60Mhz motor controller, 3 axis gyro/accelerometer chip, a 1.3 megapixel CMOS camera, 6 high-torque/titanium gear motors in the legs and an external urethane foam casing to protect the robots internal PC and equipment from shock, as shown in the right-upper window of Figure 1. The onboard PC computer provides a 16 gigabyte hard disk and two USB ports, which connect a wireless adaptor and an additional flash drive. The onboard PC computer hidden in its torso allows us to run programs under Windows or Linux operating systems, to develop programs in C++ and Python, and to control the robot motion real-time or based on predefined behaviors. For this study, we implement three robot walking behaviors: turning right, turning left and walking forward (see Section 3).

2.3 CCD Camera

The camera used in our system is a Cannon VC-C50i communication camera, as shown in the left window of Figure 1. This camera provides high-speed high-precision head movement and noise reduction circuitry for crystal clear images. It is capable of shooting at low light levels down to 1 lux. The built-in infrared light allows shooting even at 0 lux (night mode). The CCD camera takes video clips on the subject's or the instructor's hand postures to identify mental activities which are correlated to the robot walking behaviors.

3. Implementation of Walking Behaviors

The KT-X PC robot uses twelve motors to control its two legs and feet for walking. The robot is equipped with 3 axis gyro/accelerometer sensors to control walking in balance. At low level, a cubic interpolation algorithm is implemented to generate trajectories from one configuration to another. In this study, we define three walking behaviors: turning right, turning left, and walking forward. Each of these behaviors consists of a sequence of robot configurations in balance. For example, one full step walking forward can be described by the following configurations:

Gravity Right → Left Leg Up → Left Leg Forward → Left Leg Down → Gravity Left → Right Leg Up → Right Leg Forward → Right Leg Down.

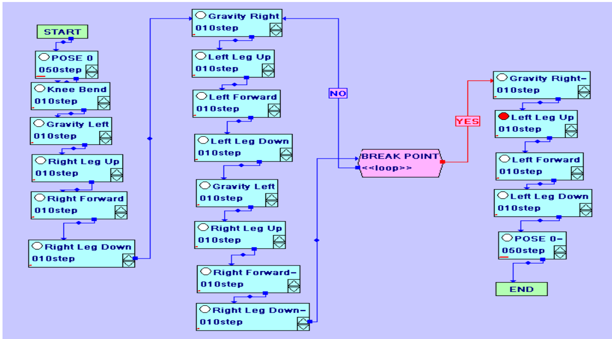
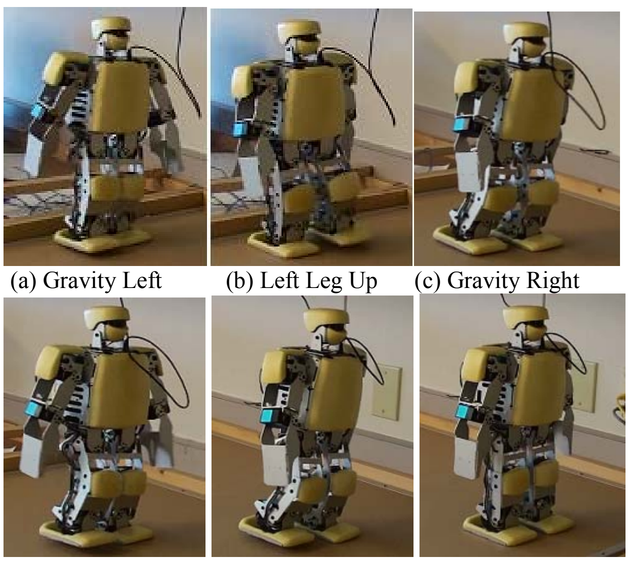


Figure 2. Implementation of the walking forward behavior in RM2



(a) Gravity Left (b) Left Leg Up (c) Gravity Right

(d) Right Leg Up (e) Right Leg Forward (f) Right Leg Down

Figure 3. Configurations of the robot walking forward behavior

In order to implement the configurations, we develop the robot kinematics in terms of Denavten-Hartenberg notation as follows

$$T_L^0 = T_1^0 T_3^1 T_5^3 T_7^5 T_9^7 T_{11}^9 T_L^{11} \qquad (1)$$

$$T_R^0 = T_2^0 T_4^2 T_6^4 T_8^6 T_{10}^8 T_{12}^{10} T_R^{12} . \qquad (2)$$

Equations (1)-(2) describe the translation and rotation relationship from the midpoints on the bottom of two feet to the midpoint on the torso of the robot. The matrix T_k^i describes the transformation from the coordinate system $\{k\}$ to the coordinate system $\{i\}$, including a rotation matrix R_k^i and translation vector ${}_k^iP$. Here, we define the coordinate systems $\{0\}$ as the reference system whose origin is located at the midpoint on the torso, and $\{L\}$ and $\{R\}$ at the midpoints on the bottom of left and right foot. The six coordinate systems with odd numbers $\{1\}$, $\{3\}$, $\{5\}$, $\{7\}$, $\{9\}$, and $\{11\}$ describe the robot's left hip, left knee, left ankle, and so on; and the other six coordinate systems with even numbers $\{2\}$, $\{4\}$, $\{6\}$, $\{8\}$, $\{10\}$, and $\{12\}$ describe their right counterparts. Figure 2 shows the implementation of the walking forward behavior using the accompanying software RobovieMaker2 (RM2), and Figure 3 displays the scenario of robot forward walking. Similarly, we also implement both of the turning left and right walking behaviors. Robot walking can be controlled by either a separate computer or the on-board PC using a USB cable or a wireless adapter. A real-time motion control program in C++ loads the motion files of the robot walking behaviors created by the RM2 software and sends them to a micro-controller to control robot walking by a serial communication port.

4. Walking Behavior Control Using Brainwaves

The idea of controlling robots or prosthetic devices by mere "thinking" (i.e., the brain activity of human subjects) has fascinated researchers over the last couple of years [3]-[12]. Biological studies provide the useful research results to understand motor cortex of human brain. The foundation of robot control using brainwaves is the motor-related rhythms. Scalp recorded electroencephalogram signals (EEG) reflect the combined synaptic and axonal activity of groups of neurons whose features can be used to control robot activities [15].

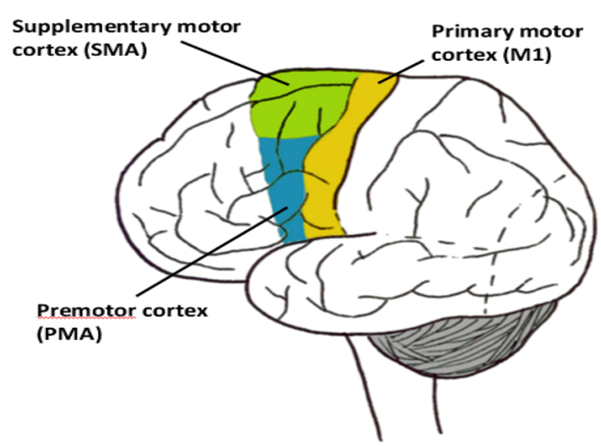


Figure 4. Motor cortex

4.1 Motor Cortex

The primary motor cortex (also known as M1), a strip located on the precentral gyrus of the frontal lobe shown in Figure 4, is an important brain region for the control of movement in humans. M1 maps the body topographically, meaning that the ventral end of the strip controls the mouth and face and the other end the legs and feet, with the rest of the body represented in between. The amount of representation is not proportional to the size of the body part. For example, the trunk is represented by only a

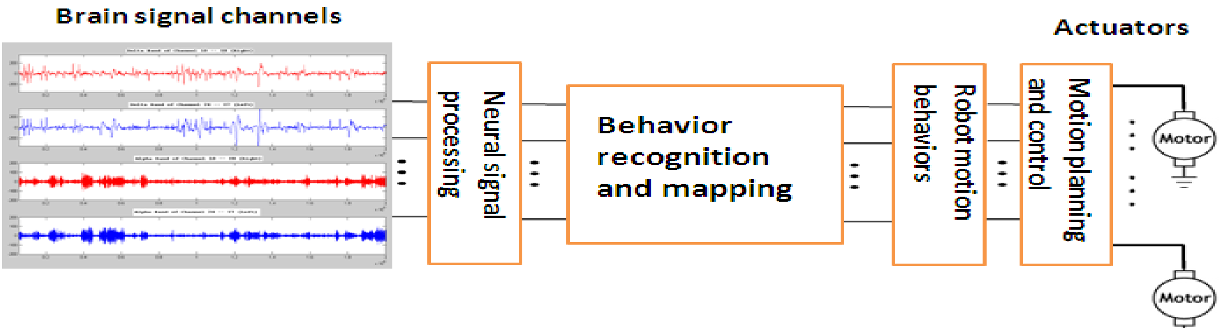


Figure 5. Control scheme for walking behaviors

small region on the primary motor cortex, because humans do not generally use the trunk for fine, precise movements or a wide range of motion. On the other hand, the fingers are greatly represented on M1, because the fingers are sensitive appendages and are used for many different movements. The primary motor cortex is thought to control both muscles and movements [16].

The nonprimary motor cortex is located just adjacent to the primary cortex and is important in the sequencing of movements. The premotor cortex (PMA) has been implicated in movements that require external cues. This region also contains mirror neurons, which are activated both when one is performing a movement and when he or she is observing someone else do the same movement; in this case, the brain is utilizing visual cues [17]. In contrast, the supplementary motor area (SMA) is utilized for movements that are under internal control, such as doing some sort of action from memory [18].

4.2 Control Scheme

Figure 5 shows a scheme for BCI-based control of the KT-X PC robot. The Cerebus™ Data Acquisition System acquires neural signals from 32-channels through an electrode cap on scalp. The neural signal processing section filters out high frequency noise and decomposes the filtered signals into delta, theta, alpha, and beta bands with a group of band-pass filters or wavelet filters [7]. The behavior recognition and mapping section recognizes the mental activities based on neural signal patterns to control the robot walking behavior. Behavior recognition and mapping section includes a C-means classification and neuro-fuzzy network. In this preliminary study, however, we use the features of phase relationship between neural signals acquired on the left brain and right brain to control robot walking forward, turning left or turning right. The robot motion behavior section sends the corresponding motion file to a micro-controller which controls 20 actuators on the robot. Trajectory planning section at low level on the micro-controller implements a cubic interpolation algorithm to generate robot motion trajectories between the configurations defined for the robot walking behaviors.

4.3 Signal Preprocessing

First, we use a low-pass filter to filter out high-frequency noise from neural signals recorded by the EEG system and then decompose the brainwaves into delta-band [0–4 Hz], theta-band [4–8 Hz], alpha-band [8–13 Hz], and beta-band [13–30 Hz]. The decomposition can be done with a group of filters or through a Discrete Wavelet Transform (DWT) [19]. The work [20] summarizes the characteristics of brainwave rhythms. The amplitude of theta waves is greatest when a person is in an inattentive mental state, such as that just before falling asleep. Theta wave amplitude is also increased momentarily by blinking or other eye movements. Alpha wave amplitude is greatest when a person is in a state of “unfocused attention,” such as during meditation. Beta wave amplitude is greatest when a person is concentrating or in an agitated state. The left-most block in the control scheme of Figure 5 shows the delta and alpha waves recorded at electrode T8 (channel 10 – right brain location) and T7 (channel 24 – left brain location).

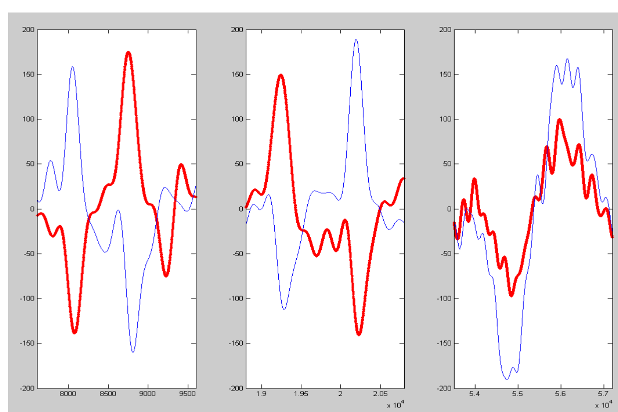


Figure 6. Patterns of brain activities

4.4 Patterns

In order to control the robot walking behaviors using neural signals, we need to generate patterns by extracting

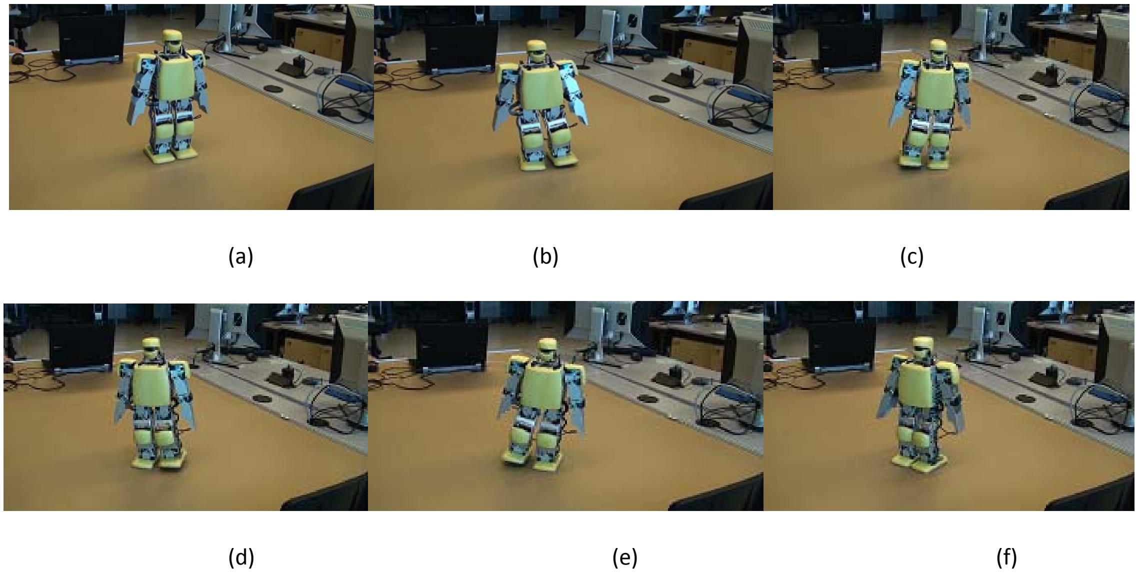


Figure 7. Control of robot turning left through brainwaves

the features of the acquired neural signals according to human mental activities. A complete analysis that takes into account average energy in time domain or signal spectrum (magnitude and phase) in frequency domain would result in a very large number of features and consequently a high dimensional feature vector [14]. In order to reduce computation complexity, some methods for extracting the features of brainwaves are proposed to lower dimensions of feature vectors. The work [21] uses EEG alpha rhythm to control a mobile robot. The work [8] evaluated four classification methods, including the PNN delta band method, to extract the features of mental activities.

Through our study, we note that the features of mental activities affect the phase relationship of neural signals recorded from neurons from the left brain and right brain. Figure 6 shows three group of delta-band signals recorded at electrodes T7 (channel 24) and T8 (channel 10), which are plotted by blue-thin (left) and red-thick curves (right), respectively. These brainwaves are correlated to the three mental activities: turning right, turning left, and walking forward. The left pattern shows the brain activity when the human subject thinks “turning right.” For this pattern, the phase of brain signals at T7 is leading to the one of brain signals at T8. The middle pattern shows the brain activity when the human subject thinks “turning left.” For this pattern, the phase of brain signals at T8 is leading to the one of brain signals at T7. The right pattern shows the brain activity when the human subject thinks “walking forward.” In this case, the difference between both phases of brain signals at T7 and T8 are close to zero. These brain activities are verified by the video clips taken by the CCD camera during the subject tests. Our further investigation discovers that the brainwaves recorded at electrodes FT7, T7, and TP7 on the left half scalp (channel 25, 24, and 18) are very similar; while the brainwaves recorded at electrodes FT8, T8, and TP8 on the right half scalp (channel 17, 10, and 9) are very similar. In order to control robot walking behaviors: turning right, turning left, and walking forward, we use the difference of the fundamental phases between T7 and T8, FT7 and FT8, and TP7 and TP8:

$$
\begin{aligned}
&\Delta phase_{T8}^{T7} = T7\_phase - T8\_phase \\
&\Delta phase_{FT8}^{FT7} = FT7\_phase - FT8\_phase \\
&\Delta phase_{TP8}^{TP7} = TP7\_phase - TP8\_phase\,.
\end{aligned} \tag{3}
$$

4.5 Control Algorithms

We develop a pattern recognition algorithm for control of the robot walking behaviors. The algorithm consists of two parts. The first part is to calculate the fundamental phase of brain signals:

Step 1: Extract delta-band rhythms from the brainwaves acquired at electrodes T7, FT7, and TP7 on the left half scalp and at electrodes T8, FT8, and TP8 on the right half scalp.
Step 2: Cut off the delta-band rhythms use a threshold ε.
Step 3: Find out a peak with maximum and a peak with minimum for each delta-band rhythm.

Step 4: Determine a common window size based on the peaks.
Step 5: Calculate the fundamental of the brain signal using FFT within the window.
Step 6: Calculate the difference of the fundamental phases using Eq. (3).

The second part of the algorithm is to use fuzzy rules to determine the robot walking behaviors:

If $\Delta phase_{T8}^{T7}$ *is near positive 180° and* $\Delta phase_{FT8}^{FT7}$ *is near positive 180° and* $\Delta phase_{TP8}^{TP7}$ *is near positive 180°*
Then *make the robot turning right*
If $\Delta phase_{T8}^{T7}$ *is near negative 180° and* $\Delta phase_{FT8}^{FT7}$ *is near negative 180° and* $\Delta phase_{TP8}^{TP7}$ *is near negative 180°*
Then *make the robot turning left*
If $\Delta phase_{T8}^{T7}$ *is near zero and* $\Delta phase_{FT8}^{FT7}$ *is near zero and* $\Delta phase_{TP8}^{TP7}$ *is near zero*
Then *make the robot walking forward*
Else *stop the robot*

Figure 7 shows that control of robot to make left turn through the recorded brainwaves.

5. Experiments

We use a 32 channel EEG to record human brain activities of thinking "turning right," "turning left" and "walking forward" for control of the humanoid robot walking behavior. We design two sets of experiments. The procedure for the first set of experiments is described as follows. When the subject starts thinking "turning right," "turning left" or "walking forward" the subject moves the right hand, the left hand, or both hands, respectively. These hand postures are synchronously taken by the CCD camera. We use these hand postures to analyze the features of brainwaves by identifying mental activities of thinking "turning right," "turning left" and "walking forward." In this experiment, the recorded brainwaves may include muscular signals caused by the subject's hand movements.

The second set of the experiment is designed as follows. The subject starts thinking "turning right," "turning left" or "walking forward" following an instructor's voice commands "turning right," "turning left" or "walking forward." At the same time, the instructor moves the right hand, the left hand, or both hands, respectively. In this experiment, the CCD camera takes synchronously the instructor's hand postures which are used to analyze the features of brainwaves correlated to the mental activities. The second set of experiments may exclude muscular signals.

6. Conclusion

This paper develops a BCI based humanoid robot control system which can serve as a platform to investigate a relationship between complex humanoid robot behaviors and human mental activities. The BCI system can be used to control the robot walking behaviors both off-line and on-line. This paper also reports our preliminary test on control of the robot walking behaviors through human brainwaves. The detail analysis on the experiments data will be presented in another paper. In order to validate the proposed control algorithms, a number of experiments are planned.

Our experiments show that the recorded data quality highly depends on subject concentration on mental activities. Now, we are developing a training module to improve the subject concentration on mental activities.

Control of the three humanoid walking behaviors may not be difficult. Our further research will control more robot activity behaviors through brainwaves, such as shifting left, shifting right, lifting left or right arms, and moving the head. For this application, we need to investigate comprehensive algorithms for recognizing human brain activities.

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