Acquiring Neural Signals for Developing a Perception and Cognition Model

Wei Li[a], Yunyi Li[b], Genshe Chen[c], Dan Shen[c], Erik Blasch[d], Khanh Pham[e], Robert Lynch[f]

[a]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

[b]Department of Psychology and Neuroscience, Duke University
417 Chapel Drive, Durham, NC 27708-0086, USA

[c]I-Fusion Technologies, Inc, Germantown, MD 20874

[d]AFRL/RIEA, Rome, NY USA 13441

[e]Air Force Research Laboratory, Space Vehicles Directorate, Kirtland AFB, NM, USA 87117

[f]Naval Undersea Warfare Center, Newport, RI, USA

ABSTRACT

The understanding of how humans process information, determine salience, and combine seemingly unrelated information is essential to automated processing of large amounts of information that is partially relevant, or of unknown relevance. Recent neurological science research in human perception, and in information science regarding context-based modeling, provides us with a theoretical basis for using a bottom-up approach for automating the management of large amounts of information in ways directly useful for human operators. However, integration of human intelligence into a game theoretic framework for dynamic and adaptive decision support needs a perception and cognition model. For the purpose of cognitive modeling, we present a brain-computer-interface (BCI) based humanoid robot system to acquire brainwaves during human mental activities of imagining a humanoid robot-walking behavior. We use the neural signals to investigate relationships between complex humanoid robot behaviors and human mental activities for developing the perception and cognition model. The BCI system consists of a data acquisition unit with an electroencephalograph (EEG), a humanoid robot, and a charge couple CCD camera. An EEG electrode cup acquires brainwaves from the skin surface on scalp. The humanoid robot 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 CCD camera takes video clips of the human subject's hand postures to identify mental activities that are correlated to the robot-walking behaviors. We use the neural signals to investigate relationships between complex humanoid robot behaviors and human mental activities for developing the perception and cognition model.

Keywords: BCI system, humanoid robot, neural signal processing, mind based control, perception and cognition model

1. INTRODUCTION

A Brain Computer Interface (BCI) affords a new communication channel that 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 the signals into device-controlled commands.

Recently, there has been an increasing interest in BCI applications to control robots through neural signals. The works in [3]-[5] propose and review directly employing cortical neurons to control a robotic manipulator. The research groups

Sensors and Systems for Space Applications V, edited by Khanh D. Pham, Joseph L. Cox,
Richard T. Howard, Henry Zmuda, Proc. of SPIE Vol. 8385, 83850I · © 2012 SPIE
CCC code: 0277-786X/12/$18 · doi: 10.1117/12.918767

cited in [6]-[8] report the navigation of mobile robots using BCI, including the control of a wheelchair in [9]-[11]. Bell et al., [12], present an example of humanoid robot control through a BCI system.

Comparing 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 [12], 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 industrial assistance in dirty or dangerous jobs. However, for people with severe motor disabilities it is important to establish augmentative communication with humanoid robots for personal assistance [13].

This paper presents a brain-computer-interface (BCI) based humanoid robot control system [15], 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 a perception and cognition model's performance for controlling humanoid walking behaviors through brainwaves.

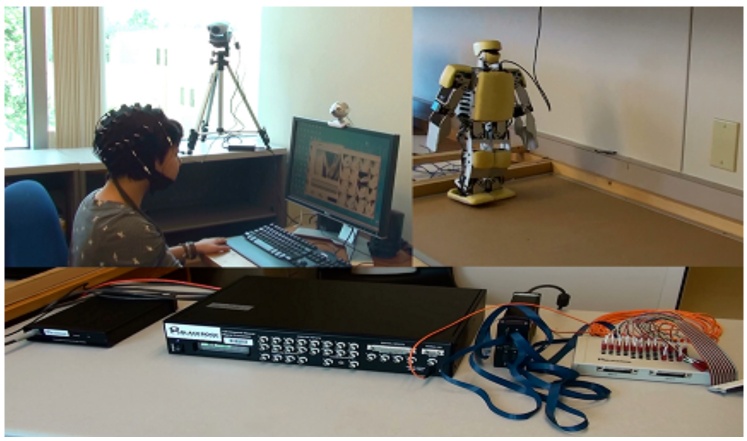


Figure 1. BCI-based humanoid robot control system

In this paper, we report on implementation of three types of robot-walking behavior: 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 experiments on recording brainwaves during mental activities. The experimental procedure is to record human subjects' mental activities when the subjects imagine "turning right," "turning left" and "walking forward." The subjects simultaneously move their right hands, left hands, and both hands when imagining "turning right," "turning left" and "walking forward." We present the recorded brainwaves of three human subjects and use an example to discuss how to extract the neural signal features for the proposed perception and cognition model.

This paper is organized in five sections. Section 2 introduces the BCI-based humanoid robot system. Section 3 describes the procedure of acquiring brainwaves. Section 4 analyzes brainwaves to investigate their features for the perception and cognition model and presents an example of controlling the humanoid robot walking behaviors through the brainwaves. Finally, Section 5 draws conclusions on the BCI-based humanoid robot system and proposes further research.

2. BCI-BASED CONTROL SYSTEM

1.1 Data Acquisition System

Our BCI interface is a Cerebus^{TM} Data Acquisition System with a 32 microelectrodes cap. The Cerebus^{TM} 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. In this system, the BCI interface is used to record brainwaves during human mental activities.

1.2 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 types of robot-walking behavior: “turning right,” “turning left,” and “walking forward.”

1.3 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 operating at low light levels down to 1 lux. The built-in infrared light allows extended viewing 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 that are correlated to the robot-walking behaviors.

3. ACQUISITION OF 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 useful research results to understand motor cortex of human brain. The foundation of robot control using brainwaves is the motor-related brain rhythms. Scalp recorded electroencephalogram (EEG) signals reflect the combined synaptic and axonal cortical activity of groups of neurons whose features can be used to control robot activities [16].

The primary motor cortex (also known as M1), a strip located on the precentral gyrus of the frontal lobe shown in Figure 2, 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 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 [17].

The nonprimary motor cortex, consisting of the premotor cortex (PMA) and supplementary motor area (SMA), is located just adjacent to the primary cortex and is important in the sequencing of movements. The PMA has been implicated in movements that require external cues. The PMA 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 [18]. In contrast, the SMA is utilized for movements that are under internal control, such as doing some sort of action from memory [19]. We envision that the M1, PMA, and SMA as essential areas for neuron activity for perceptual and cognitive control that are monitored by an EEG.

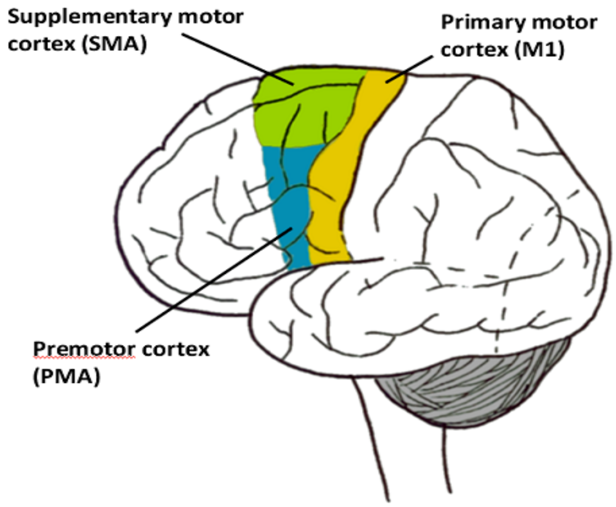
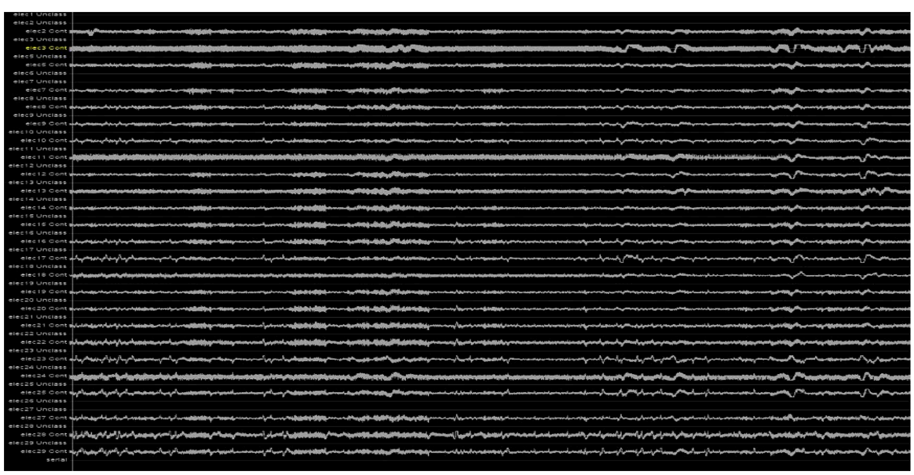
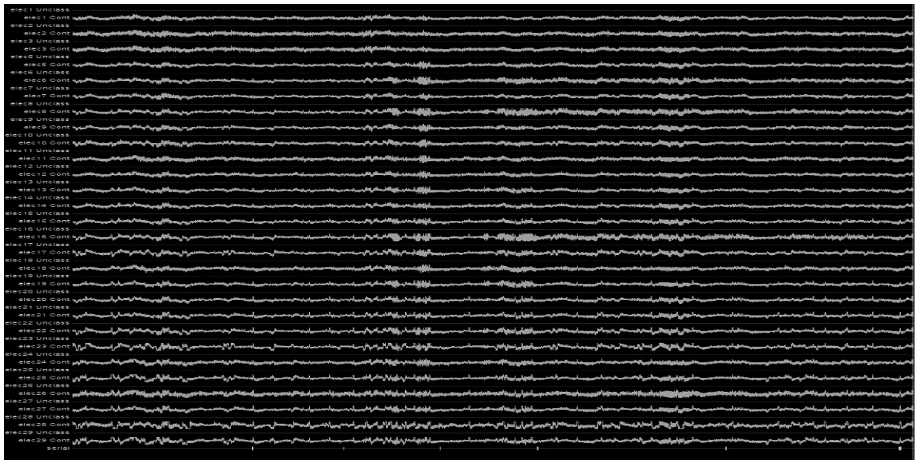


Figure 2. Motor cortex

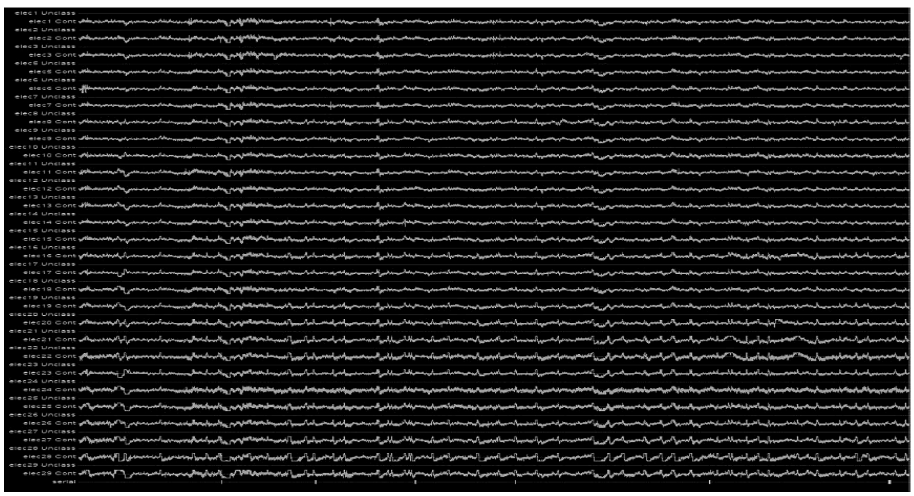
We use a 32 channel EEG to record human brain activities of imagining "turning right," "turning left" and "walking forward" for control of the humanoid robot-walking behaviors. The procedure of experiments is described as follows. When a human subject starts imagining "turning right," "turning left" or "walking forward" the subject simultaneously moves its right hand, left hand, or both hands, respectively. The CCD camera synchronously takes these hand postures. Figures 3a-3c show the brainwaves of three human subjects that are recorded during the three human mental activities. We use these brainwaves to investigate relationships between complex humanoid robot behaviors and human mental activities. However, recognizing a certain robot-walking behavior from the brainwaves (decoding brainwaves) is a very challenging task. We use these hand postures in the video clips to determine the time intervals for mental activities of imagining "turning right," "turning left" or "walking forward" and further analyze brainwave features for the perception and cognition model. It should be noted that the brainwaves of the three human subjects look significantly different although all they are correlated to the same mental activities of imagining the three robot-walking behaviors.



(a): Human subject 1.



(b): Human subject 2.



(c): Human subject 3.

Figure 3. The brainwaves of three human subjects recorded during the mental activities of imagining the robot-walking behaviors.

4. CONTROL OF HUMANOID ROBOT

Figure 4 shows a scheme for BCI-based control of the KT-X PC robot. The Cerebus^{TM} 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 that represents the perception and cognition model recognizes the mental activities based on neural signal patterns to control the robot-walking behavior. The perception and cognition model includes a C-means classification algorithm and a neuro-fuzzy network. The implementation of this model proceeds from these following steps. First, extract the brainwave features of a human's mental activities, including the signal phases, signal magnitudes, signal powers and energies, etc. Second, classify these features using the C-means classification algorithm. Finally, establish the relationship between the brainwave features and the robot-walking behaviors using the neuro-fuzzy network. This model operates in off-line and on-line phases. During the off-line phase, we use the brainwave features to train the neuro-fuzzy network because the features of the human subjects may be different from one to another. During the on-line phase, we use the trained model to select on-line the corresponding robot-walking behavior according to a subject mental activity.

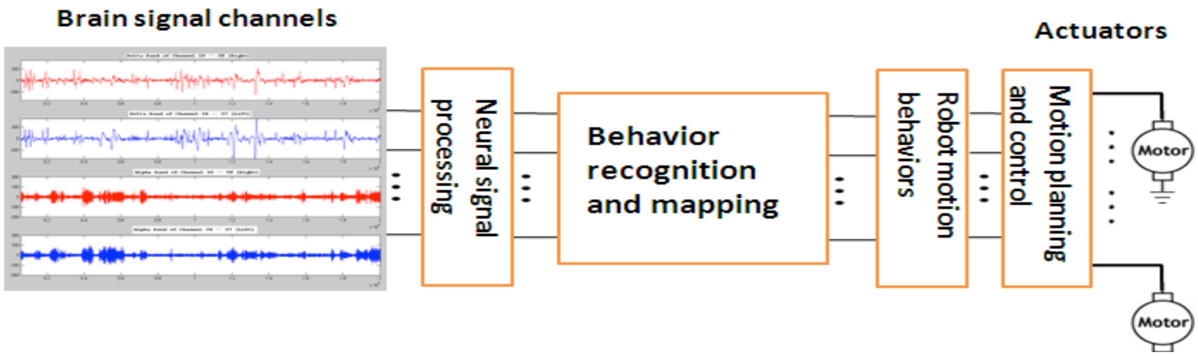


Figure 4. Control scheme for walking behaviors

A great deal of work needs to be done for understanding the brainwaves features and generating patterns by extracting the features of the acquired neural signals according to human mental activities. A complete analysis that takes into account average energy in the time domain, or signal spectrum (magnitude and phase) in the frequency domain, would result in a very large number of features and consequently a high dimensional feature vector [13]. In order to reduce the computational complexity, some methods for extracting the features of brainwaves are proposed to lower the dimension of the feature vectors.

In this preliminary study, we use the features of phase relationship between neural signals acquired on the left and right locations on scalp to control robot-walking forward, turning left or turning right. The robot motion behavior section sends the corresponding motion file to a micro-controller that controls 20 actuators on the robot. Trajectory planning section at low level on the micro-controller implements a cubic-spline interpolation algorithm to generate robot motion trajectories between the configurations defined for the robot-walking behaviors. To conduct the phase analysis, we process the neural signals.

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) [20]. The work in [21] 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. The Theta wave amplitude is also increased momentarily by blinking or other eye movements. The Alpha wave amplitude is greatest when a person is in a state of “unfocused attention,” such as during meditation. The Beta wave amplitude is greatest when a person is concentrating or in an agitated state. As an example, the left-most block in the control scheme of Figure 5 shows the delta waves recorded at electrode T8 (channel 10 – right brain location) and T7 (channel 24 – left brain location) from the brainwaves of subject 1 in Figure 3a.

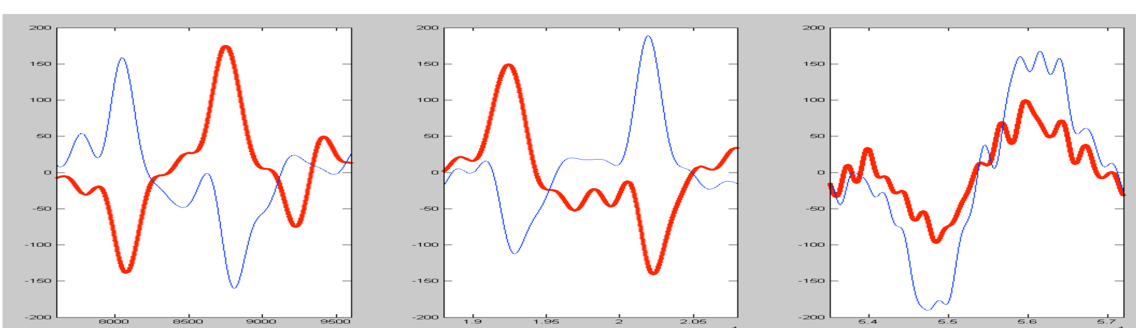
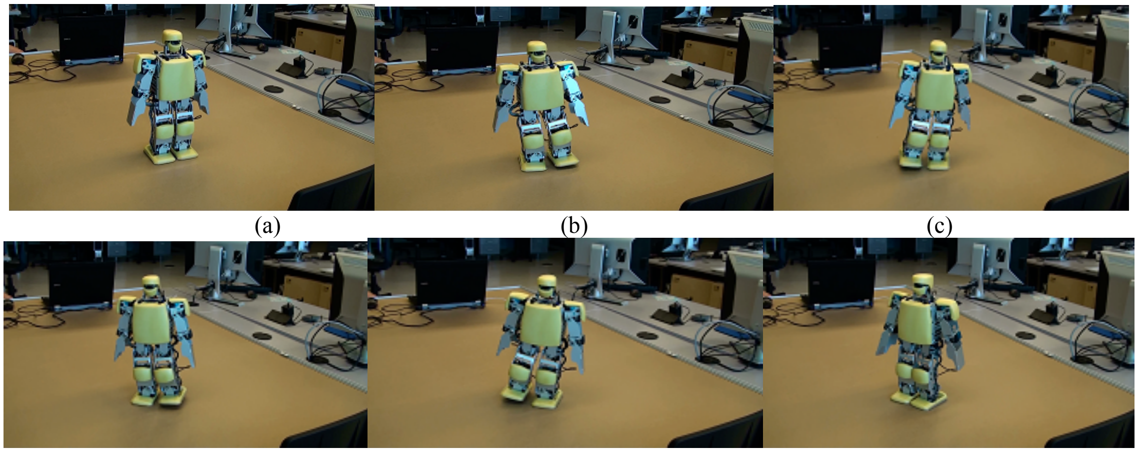


Figure 5. Mental activities’ patterns of subject 1 (T7 – blue, T8 – red),
Thinking activities: A. Turning Right, B. Turning Left, C. Moving forward.



(a) (b) (c) (d) (e) (f)

Figure 6. Control of robot turning left through brainwaves

Our study indicates that the features of mental activities for humanoid robot control affect the phase relationship of neural signals recorded from neurons from the left brain and right brain. Figure 5 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 Figure 5 when the human subject is thinking "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 is thinking "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 is thinking "walking forward." In this case, the difference between both phases of brain signals at T7 and T8 are close to zero. The video clips taken by the CCD camera during the subject tests verify these brain activities. 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. In order to test the feasibility of the BCI-based humanoid robot system, we use the patterns extracted from the brainwaves of subject 1 to control the robot-walking behaviors as shown in Figure 6 [14]. We note that the mental activities' patterns of brainwaves correlated to the robot-walking behaviors are distinguished from person to person. Therefore, it is necessary to train the neuro-fuzzy network in the behavior recognition and mapping section through the patterns of an individual subject before an individual controls the robot-walking behaviors through his brainwaves.

5. CONCLUSION

This paper presents 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 detailed analysis on the experimental data will be presented in our further work. In order to validate the proposed BCI-based humanoid robot system, a number of experiments are planned. We have shown a simple perception and cognitive model that links the perceptual brain activities (e.g.. brainwaves) with the cognitive mental activities of virtual control of a humanoid robot.

In this paper, we use the subjects' hand postures recorded in video clips to identify the subjects' mental activities. In this case, however, the recorded brainwaves may include muscular signals caused by the subject's hand movements. How to recognize the subjects' mental activities from their brainwaves is a very challenging task, especially in the case of "pure imagination" of a robot-walking behavior. Our experiments show that the recorded data quality highly depends on subject concentration on mental activities. Currently, we are developing a virtual environment to improve 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 that afford humanoid control.

REFERENCES

[1] Millán J. d. R., *Brain-Computer Interfaces, Handbook of Brain Theory and Neural Networks,* 2nd ed., Cambridge, MA, The MIT Press, (2002).

[2] Schalk G., McFarland D. J., Hinterberger T., Birbaumer N., and Wolpaw J. R., "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Transactions on Biomedical Engineering*, 51(6), 1034-1043 (2004).

[3] Chapin J. K., Moxon K. A., Markowitz R. S., and Nicolelis M. A. L., "Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex," *Nature Neuroscience,* 2, 664-670 (1999).

[4] Wessberg J., Stambaugh C. R., Kralik J. D., Beck P. D., Laubach M., Chapin J. K., Kim J., Biggs S. J., Srinivassan M. A., and Nicolelis M. A. L., "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature,* 408, 361-365 (2000)

[5] Lebedev M. A. and Nicolelis M. A. L., "Brain-machine interfaces: past, present and future," *Trends in Neurosciences*, 29, 536-546 (2006).

[6] Millán J. d. R., Renkens F., Mouriño J., and Gersterner W., "Noninvasive brain-actuated control of a mobile robot by human EEG," *IEEE Transactions on Biomedical Engineering*, 51(6), 1026-1033 (2004).

[7] Tanaka K., Matsunaga K., and Hori S., "Electroencephalogram-based control of a mobile robot," *Electrical Engineering in Japan*, 152(3), 39-46 (2005).

[8] Barbosa A. O. G., Achanccaray D. R., and Meggiolaro M. A., "Activation of a mobile robot through a brain computer interface," *Proc. of 2010 IEEE International Conference on Robotics and Automation*, 4815-4821 (2010).

[9] Rebsamen B., Burdet E., Guan C., Teo C. L., Zeng Q., and Laugier M. A. C., "Controlling a wheelchair using a BCI with low information transfer rate," *Prof. of IEEE 10th International Conference on Rehabilitation Robotics*, 1003-1008 (2007).

[10] Galán F., Nuttin M., Lew E., Ferrez P. W., Vanacker G., Philips J., and Millán J. d. R., "A brain- actuated wheelchair: Asynchronous and non-invasive Brain–computer interfaces for continuous control of robots," *Clinical Neurophysiology*, 119(9), 2159-2169 (2008).

[11] Iturrate I., Antelis J. M., Kubler A., and Minguez J., "A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation," *IEEE Transactions on Robotics*, 25(3), 614-627 (2009).

[12] Bell C. J., Shenoy P., Chalodhorn R., and Rao R. P. N., "Control of a humanoid robot by a noninvasive brain-computer interface in humans," *Journal of Neural Engineering*, 5(2), 214-220 (2008).

[13] Hirai K., Hirose M., Haikawa Y., and Takenaka T., "The development of Honda humanoid robot," *Proc. of 1998 IEEE International Conference on Robotics and Automation*, 2, 1321-1326 (1998).

[14] Wolpaw J. R., McFarland D. J., and Vaughan T. M., "Brain computer interface research at the Wadsworth Center," *IEEE Transactions on Neural Systems and Rehab. Eng.,* 8, 222-226 (2000).

[15] Li W., Jaramillo C., and Li Y., "A brain computer interface based humanoid robot control system," *Proc. of the IASTED International Conference on Robotics (Robo 2011),* 390-396 (2011).

[16] Garcia G. N., *Direct brain-computer communication through scalp recorded EEG signals*, Doctor's thesis, Department of Electricity, Ecoloe Polytechnique Federale de Lausanne, Switzerland, (2004).

[17] Breedlove M., Rosenweig M., and Watson N., *Biological Psychology: An Introduction to Behavioral, Cognitive, and Clinical Neuroscience*. Sianuer Associates, Inc., Sunderland, MA. (2007).

[18] Buccino G., Lui F., Canessa N., and Patteri I., et al., “Neural circuits involved in the recognition of actions performed by nonconspecifics: An fMRI study,” *Journal of Cognitive Neuroscience,* 16, 114-126 (2004).
[19] Halsband U., Matsuzaka Y., and Tanji J., “Neuronal activity in the primate supplementary, pre-supplementary and premotor cortex during externally and internally instructed sequential movements,” *Neuroscience Research,* 20, 149-155 (1994).
[20] Jahankhani P., Kodogiannis V., Revett K., “EEG signal classification using wavelet feature extraction and neural networks,” *Proc. of IEEE John Vincent Atanasoff 2006 International Symposium on Modern Computing*, 120-124 (2006).
[21] Amai W., Fahrenholtz J., and Leger C., “Hands-free operation of a small mobile robot,” *Autonomous Robots*, 11(1), 69-76 (2001).