35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

An SSVEP Based BCI to Control a Humanoid Robot by Using Portable EEG Device

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Abstract— **Brain Computer Interfaces (BCIs) are systems that allow human subjects to interact with the environment by interpreting brain signals into machine commands. This work provides a design for a BCI to control a humanoid robot by using signals obtained from the Emotiv EPOC [11], a portable electroencephalogram (EEG) device with 14 electrodes and sampling rate of 128 Hz. The main objective is to process the neuroelectric responses to an externally driven stimulus and generate control signals for the humanoid robot Nao accordingly. We analyze steady-state visually evoked potential (SSVEP) induced by one of four groups of light emitting diodes (LED) by using two distinct signals obtained from the two channels of the EEG device which reside on top of the occipital lobe. An embedded system is designed for generating pulse width modulated square wave signals in order to flicker each group of LEDs with different frequencies. The subject chooses the direction by looking at one of these groups of LEDs that represent four directions. Fast Fourier Transform and a Gaussian model are used to detect the dominant frequency component by utilizing harmonics and neighbor frequencies. Then, a control signal is sent to the robot in order to draw a fixed sized line in that selected direction by BCI. Experimental results display satisfactory performance where the correct target is detected 75% of the time on the average across all test subjects without any training.**

I. INTRODUCTION

Electroencephalogram (EEG) based Brain Computer Interface (BCI) technology is a field of research which grows in an expeditious manner due to the usability and cost effectiveness of EEG as compared to other brain activity monitoring techniques. The advances in computer technology, mechanics and electronics lead the development of humanoid robots which can perform many skillful tasks such as manipulating objects and servicing. EEG based BCI applications provide a link between the thoughts of a person and these skillful robots without any physical contact. There are various BCI-based control systems for robots using different brain signals obtained from EEG, such as Event Related Potential (ERP) for humanoid robot walking, steady-state visually evoked potential (SSVEP) for manipulating table-top objects [1], P300 evoked potential for robot navigation [2], controlling a virtual hand [10] and manipulation of objects [12].

Previous works on using EEG devices for BCI vary according to the used EEG device, which are often not portable and have a large number of channels with high sampling frequencies. The main objective of SSVEP based BCI's is to determine control signals from the EEG data, but the response to a stimulus can change from user to user. In order to reduce personal differences, previously proposed systems [4] [3] require some training. The training results are used to determine user specific flicker frequency, amplitude threshold or FFT window size.

In this study, we use SSVEP signals to control a humanoid robot to draw a square. Our aim is to eventually develop a platform to help disabled people to communicate with home assistant robots or other machines. SSVEP is chosen due to its many benefits over other systems, one of which being its high information transfer rate (ITR) with little or no user training. Our proposed BCI employs a portable EEG device since its design is suitable for public usage and has advantages such as low cost together with higher levels of user comfort. We did not prefer to use Emotive cube interface since it requires long training sessions and high concentration of the user. However, since the device has low sampling rate and noisy sampling which result in weak responses to the stimuli, we use LEDs to generate stimuli instead of a computer monitor in order to improve the system performance. We propose a Gaussian model solution to calculate a weighted sum for each frequency by considering neighbor frequencies and harmonics to eliminate the aforementioned problems to a degree without any training.

The organization of the rest of the paper is as follows. In Section II we describe the robotic platform used. The experimental setup is given in Section III. In Section IV the approach for the collection and analysis of the data are given. The experimental results obtained and their discussion are given in Section V. Finally, the conclusions and suggested future work are given in Section VI.

II. THE HUMANOID ROBOT NAO

Nao is a programmable, 57-cm tall humanoid robot with 25 degrees of freedom (DOF) whose key elements are electric motor actuators and various sensors[6]. A schematic diagram of the robot can be seen in the Fig.1.

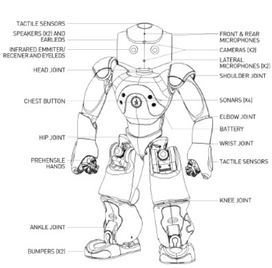

Fig. 1. Humanoid Robot Nao[7]

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For the Nao to draw the lines of a square, joint angles for each position are determined using the Choreographe software that lets users create and edit movements of the robot; it is designed and developed by Aldebaran Robotics [8]. Drawing actions are implemented using the code of Cerberus which is the Robocup SPL Team of the Artificial Intelligence Laboratory at the Department of Computer Engineering at Bogazici University [14]. In our system, the Nao waits for a message from the BCI and draws one of the lines of the square according to the determined direction as seen in Fig.2.

Fig. 2. Nao Drawing a Line of the Square

III. DESIGN OF THE EXPERIMENTS

The general control flow of the proposed BCI system can be seen in Fig.3.

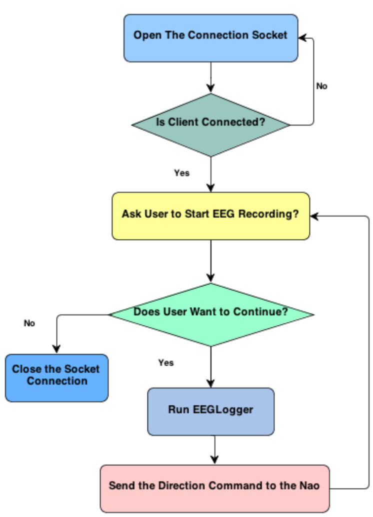

Fig. 3. BCI Control Flow Diagram

A. Experiment Setup

Initially, we considered setting up a stimulus system using a computer monitor but it limited the range of frequencies that can be used for stimulation due to the refresh rate of 60 Hz (or rates within the neighborhood of 60 Hz) on most modern monitors. The setup was changed after considering the results of a survey of stimulation methods used in SSVEP-Based BCIs; it shows that the systems that use LEDs instead of LCD monitors have higher bit rates [5]. A system is designed for generating four Pulse Width Modulated (PWM) signals by using a FreeScale MC9S12DG128B microcontroller. The frequency range of the signals is specified as 7 Hz to 17 Hz and the duty cycle is determined as 50%. Each signal is connected to one group of LEDs via a circuit that includes transistors to amplify the limited current of the microcontroller output. In order to determine the frequency of each group of LEDs, seven DIP switches on the board are used. After raising an interrupt by pressing an external button, the specified frequency is set to the selected LED group. In addition to this, a one line character LCD is used to display the current frequency values of each channel. A setup is designed for the subject to easily choose a group of LEDs that represent a specific direction command for the Nao; it can be seen in Fig.4.

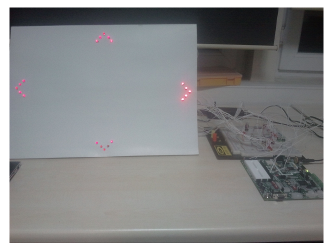

Fig. 4. The Experiment Setup For Generating Four Stimuli that Represent Directions

B. EEG Recording and Stimuli

The observer is prepared for the task by fixating at the center point and directing attention to one group of LEDs that generate a fixed frequency signal. The four different stimuli, namely left, right, down and up have frequencies 7 Hz, 9 Hz, 11 Hz and 15 Hz respectively. Odd frequencies are chosen to eliminate overlap of signals at their first and second harmonics. Initial experiments were carried out in the AILab of the Department of Computer Engineering at Bogazici University which is an unshielded public place where ambient light and noise are abundant. The results showed that the light and noise in the environment have negative influence. Then, we tried to minimize light and did the tests in a darker environment that can be seen in Fig.5. Since the power of LEDs are low, the subject is requested to focus on the selected LEDs closely. Two sets of experiments were done with 5-6 cm and 20-25 cm distance between the subject and the LEDs. In the experiments, data were recorded for five consecutive seconds, which showed clear improvement over our preliminary experiments where data were recorded for five separate seconds.

IV. DATA ANALYSIS

The raw data are taken from the Emotiv EPOC using MATLAB. For each trial, 5 seconds of EEG data were

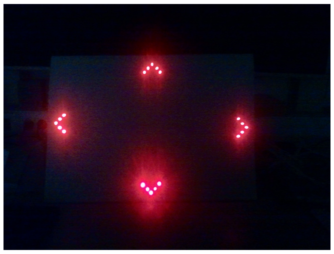

Fig. 5. LEDs with Different Flicker Frequencies that Represents 4 Directions (At Dark Room)

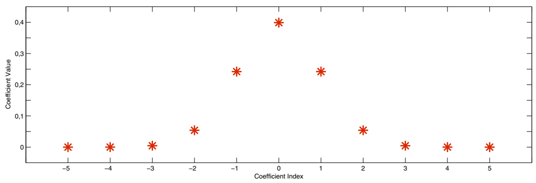

Fig. 6. 11 Gaussian Coefficients

analyzed. There are only two channels at the back of the scalp that collect data from the occipital lobe which is responsible for vision in the brain. Since SSVEP is expected to appear at the vision center, we apply Discrete Fourier Transform to the data obtained only from these two channels which are occipital left and occipital right (O1 and O2). A simple peak detection algorithm was applied, but a peak at frequency f was observed to appear in the range of $f-1$ to $f+1$ which may ultimately result in detecting the wrong stimulus frequency. For instance, while the subject is focusing at a stimulus of 7 Hz, the amplitude peak can be seen in between 6 Hz and 8 Hz instead of exactly at 7 Hz. Possible reasons include personal differences, positioning of the EEG device, low sampling rate of the device and the noise in the data. Consequently, a Gaussian model is proposed as a solution to provide robustness against this problem. In this model, 11 coefficients generated by Eq.(1) with $\sigma = 1$ and $j = -5, -4, .., 4, 5$ are used; they can be seen in Fig.6.

$$w_j = \frac{1}{\sqrt{2\pi}\sigma} \exp(-\frac{j^2}{2\sigma^2}) \quad (1)$$

The coefficients are multiplied with the neighbor frequencies around a frequency f which are $f-1.0$, $f-0.8$, $f-0.6$, ... $f+0.6$, $f+0.8$, $f+1.0$ (this method may be interpreted as Gaussian band pass filtering). Summing these 11 values provides a total weight for each LED frequency. In order to eliminate the alpha band effect on the data, harmonics of the LED frequencies are also used: The first and second harmonics and respective neighbor frequencies were multiplied by the aforementioned Gaussian model and added to the weight of corresponding frequency. The direction with the highest corresponding frequency weight is then sent to the robot as its next command. The algorithmic flow of recording and analyzing the data can be seen in Fig.7.

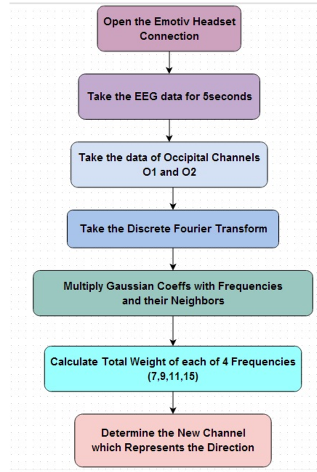

Fig. 7. Collection and Analysis of The Data

V. EXPERIMENTAL RESULTS

SSVEP power strongly depends on both the flicker frequency and the position of the stimuli as found in previous studies [13]. As seen in Fig.8, Fig.9, Fig.10 and Fig.11, there are no clear peaks at the expected frequencies. Instead, they appear at the neighboring frequencies. Furthermore, in Fig.8 comparing only the main frequencies gives an erroneous result of 15 Hz. Using our model, 7 Hz is determined as the correct frequency. The weights seen in Fig.8 show that classification based on the combined harmonics lead to a significant improvement on the accuracy; this is also mentioned in previous works [9]. The data with results seen in Table I are taken when the subject is at a 5-6 cm distance to the stimuli and directly focusing on them in the unshielded department laboratory. Adding the neighboring frequencies multiplied with Gaussian coefficients is seen to improve the performance of the system greatly compared to simple peak detection.

TABLE I
GAUSSIAN MODEL EFFECT ON ESTIMATION CORRECTNESS (12 SAMPLES AT EACH CELL)

	7 Hz	9 Hz	11 Hz	15 Hz	Average
FFT	75%	50%	33%	33%	48%
FFT + Gaussian	100%	50%	83%	50%	71%

Two sets of experiments were then carried out with three volunteer subjects with their consents. In the first experiment, the subjects were set approximately at 5 cm from the LEDs. Experimental results seen in Table II display satisfactory performance where the correct target is detected 81.7% of the time on the average. The second set was taken where subjects were approximately at a 22 cm distance. The rate of correct estimation decreased for each subject as seen in Table III.

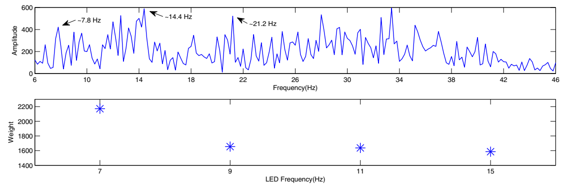

Fig. 8. FFT of Occipital Channels' Data and Frequency Weights for 7Hz

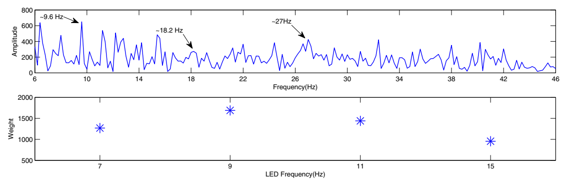

Fig. 9. FFT of Occipital Channels' Data and Frequency Weights for 9Hz

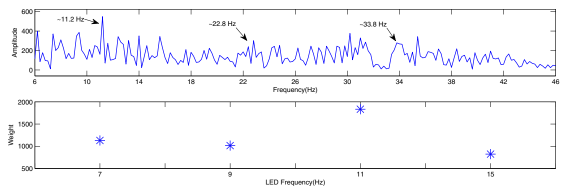

Fig. 10. FFT of Occipital Channels' Data and Frequency Weights for 11Hz

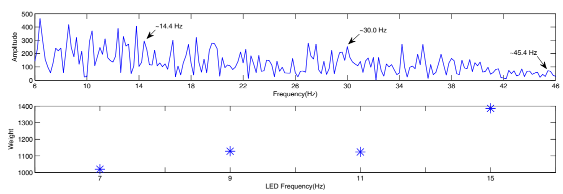

Fig. 11. FFT of Occipital Channels' Data and Frequency Weights for 15Hz

TABLE II

ESTIMATION CORRECTNESS AT 5 CM (5 SAMPLES AT EACH CELL)

Subject \ f_{LED}	7 Hz	9 Hz	11 Hz	15 Hz	Average
Subject 1	80%	100%	100%	80%	90%
Subject 2	100%	40%	100%	40%	70%
Subject 3	100%	80%	80%	80%	85%
Average	93.3%	73.3%	93.3%	66.7%	81.7%

VI. CONCLUSIONS

In this study we propose a BCI with an inexpensive and easy to use EEG to control the arm of a humanoid robot without training. Our aim is to develop eventually a platform to help disabled people to communicate with home assistant robots or other machines. The set up may be converted to an interface to choose a task for a robot such as bringing an object or turning on a device. The proposed BCI system works properly with an average success rate of 75% for all subjects with different distances from the stimuli. As future work we will use zero padding in order to increase the resolution of the FFT and decrease 5 seconds data receiving period. A more detailed analysis will be done by applying a window prior to FFT. Different stimulus frequencies will also be tested.

TABLE III

ESTIMATION CORRECTNESS AT 22 CM (5 SAMPLES AT EACH CELL)

Subject \ f_{LED}	7 Hz	9 Hz	11 Hz	15 Hz	Average
Subject 1	80%	80%	100%	20%	70%
Subject 2	40%	80%	100%	40%	65%
Subject 3	100%	60%	20%	100%	70%
Average	73.3%	73.3%	73.3%	53.3%	68.3%

ACKNOWLEDGMENTS

We would like to thank Dr. Adil Deniz Duru for valuable discussions, Ayberk Ozgur and all members of the AILab of the Department of Computer Engineering of Bogazici University for their help in the experiments, Assist. Prof. Albert A. Salah for supplying the Emotiv EPOC Headset, and Assoc. Prof. Arda Yurdakul for supplying the Freescale Microcontroller Kit.

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