Brain Computer Interface for smart living environment

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Abstract—**Brain-computer interface (BCI) provides a pathway communication between human brain and computer system. Its main goal is to allow for non-muscular communication with external world, which may be the only way for patients in a locked-in state. In this paper, many approaches are studied where users healthy brain signals are recorded using electroencephalogram (EEG) and explored in order to be able to control some smart home appliances and a robotic arm for self-feeder to help disabled persons, who cannot move or talk, to live independently in a brain-controlled environment. Specifically, the Steady State Visual Evoked Potentials (SSVEP) brain response induced by visual stimulus is used to detect at which frequency the subject is exactly looking, and at this moment the software sends the corresponding request to move the robotic arm to the desired plate to feed himself. Also, a Wi-Fi-based smart home automation is introduced, where light intensity and fan speed are controlled automatically through the physiological state of the individual without any external stimuli, or voluntary through the SSVEP method. Finally, a comfortable way is proposed to let the user choose between two options by an EEG-based color recognition (red and blue colors).**

Keywords—Brain Computer Interface (BCI), Electroencephalography (EEG), Power Spectral Density, Wavelet Decomposition, Support Vector Machines, Event-Related Spectral Dynamics (ERSP)

I. Introduction

Interaction with the outside world is one of the main existence reasons of the human being. However, this interaction cannot be realized by all people. The normal pathways to sense and express may be lost or damaged due to some accidents or diseases. For these people, also called as locked-in, Brain Computer Interfaces (BCIs) play an important role in terms of providing alternative pathways to interact with the outside world. Recently, many studies showed that scalp electroencephalographic (EEG) signals can be the basis for non-muscular communication and control systems [1].

The basic blocks of a typical BCI are: (1) Data acquisition to measure brain activity (2) Pre-processing techniques as filtering to reduce noises and artifacts, (3) Feature extraction block such as extraction of time, frequency, time-frequency or spatial domain features and (4) Classification and translation of features into commands to control applications.

Several works have been done to provide a smart living environment for the user through his brain waves as controlling home appliances based on visual stimulus as P300 speller [2] and SSVEP method [3]. Even a virtual reality is introduced to simulate home control through hybrid system BCI control [4]. Also, an eye-blink artifact augmented by a Bluetooth based indoor localization system is studied [5], [6]. Another work is an auto-adjustment home control through IoT and physiological state detection like the illumination of day and night lamps and fan speed [7].

However most of these systems used large number of channels that make them non-practical for the daily life use and few of them focused on designing a real application for environment control based on both human's voluntary intention and physiological state.

In this paper, a combination of many methods is proposed in order to design brain controlled application, where both evoked and induced brain responses of disabled person are considered, requiring only a good vision and a normal physiological state without any effort.

In terms of evoked potentials (EP) that are generated unconsciously by the participant in response to some specific external stimuli, a Steady State Visual-Evoked Potentials (SSVEP) responses to visual stimuli is designed as it has proven to be a reliable response for controlling BCI, and can be evoked across any participant [8]. This method is applied to control a robotic arm as a self-feeder and to voluntary control lighting intensity and fan speed in home. Furthermore, in terms of drowsiness and alertness induced brain activities, a research methodology for physiological state detection and tracking is explored and applied in a brain-physiologically-controlled home through a designed webserver based on NodeMCU module. In addition, brain responses to different colors; mainly the red and blue colors, are explored to predict the color at which the user is looking and thus, use this prediction to differentiate between two options choice. The designed application with these three methods studied will be discussed in the following sections.

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II. OVERALL APPLICATION

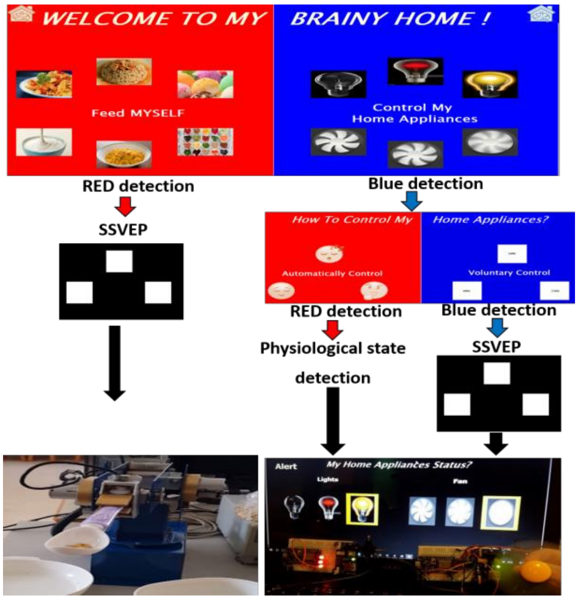

Fig. 1. UI diagram for application on robotic and home control

The User Interface (UI) designed in Visual Studio (VS) appears in Figure 1. where the user has the choice to select 'Feed MYSELF' option for robotic arm control through SSVEP, or select 'Control My Home Appliances' for brain-controlled lighting and ventilation. This choice selection is detected by red recognition for the feeding and a blue one for home control. If the software detects that the user is looking at the red color, an SSVEP form will appear to simulate the flickering box at the three pre-trained frequencies: 7.5Hz, 10Hz and 12Hz. The predicted visualized frequency will give the corresponding commands to the robotic arm to go to the desired plate. Otherwise, the blue color detection will open a new form asking him to choose between the 'Automatically Control' through physiological state or the 'Voluntary Control' through SSVEP. Similarly, the color detection is used to make the desired choice. A voluntary selection will bring him to the SSVEP form to control lighting intensity and ventilation speed by frequencies. And the automatic selection will open a new form where the user can see periodically his actual physiological state (drowsy, relaxed or alert) predicted by MATLAB and the corresponding LED and FAN behavior (OFF, ON-Medium, ON-High) on the VS application and the wirelessly connected hardware controlled via NodeMCU.

III. SSVEP DETECTION

A. Experiment Protocol

First, as data acquisition system, the OpenBCI kit [9] is chosen because it is open-source, easy portable, compatible with many important softwares. The sampling rate used is 250Hz. 8 electrodes were placed on the subject's scalp where only 3 channels from the occipital lobe O1, O2 and Oz of the international 10-20 system are studied in this experiment that stimulates the vision part of our brain; mainly in occipital regions.

Then, acquisition and training sessions were performed using OpenVIBE software where a built-in SSVEP scenario is available. Five female subjects aged between 17 and 25 were engaged in the training sessions, none of them had any known neurological deficits or visual problems. They were asked to sit in a dark room, in front of the computer monitor located 60 cm away from their eyes, and minimize their muscle movements. During each run, the subject was asked to focus on a specific target frequency pointed by a small arrow while it's blinking for 7 seconds. After each run, there was a pause of 10 seconds.

Every subject recorded four identical sessions separated by 60 seconds; each session consists of 8 runs for each of the three frequencies, and for the centered black square representing non-stimulation task. The top square frequency was set to 12Hz, 10Hz for left side square and 7.5Hz for right square. In order for the SSVEP to work, frequencies were chosen to be an entire division of our screen refresh rate 60Hz. Also these frequencies were chosen to be in the low-frequency range (4-12Hz) as it was studied to be an efficient range for SSVEP detection in many research studies [10]. The white color was chosen for the target flickering squares because it was found that white color for stimuli can lead to the highest performance, followed by gray, red, green and blue stimuli [11].

B. Proposed processing method

The proposed processing method is developed with MATLAB using the SSVEP EEG Processing toolbox. In the preprocessing stage, a band-pass filter is applied to extract EEG signals in their normal range [0.1-100Hz]. Also, an IIR elliptic filter designed in MATLAB is used to reduce the noise, and the signals are re-referenced by subtracting the mean signals. Furthermore, the 'AMUSE' algorithm is applied as eye artifact removal. The adopted feature extraction method is the PWelch power spectral density estimate where a Hamming window of 350 segment's length is applied with 50% overlapping and 512 points for the Fast Fourier Transform (FFT) calculation. The selection of features is performed by Singular Value Decomposition (SVD). The trained classifier for each subject is built using LIBSVM toolbox based on SVM classification. Finally, "Leave one sample out, given a subject" is adopted as an evaluation object of the experiment.

Then, lab streaming layer (LSL) is used to stream online the EEG data. A serial port is open between MATLAB and the robotic arm with six degree of freedom and the necessary values are sent for each rotational joint to be able to move the arm to three positions: **(1)** if the predicted class was 7.5Hz, the robotic arm will move and feed the user with the plate on the right, **(2)** if it was 10Hz, it will feed him with the plate on the left, and **(3)** if it was 12Hz, the robotic arm will go back to its initial position. Regarding home appliances control, the NodeMCU (ESP-12E) Wi-Fi chip was programmed to be a webserver having a certain IP address that receives command from any client as MATLAB in our case. Then, each predicted frequency will set the lighting intensity and the fan speed to a certain state (for example 7.5Hz for ON-High, 10Hz for ON-Medium state and 12Hz for OFF state).

C. Results

The power spectral density of the trials corresponding to each of the three frequency are collected and averaged as shown in Figure 2. Then, after classification and evaluation, the accuracy results are shown in Table I.

IV. PHYSIOLOGICAL STATE DETECTION

A. Experiment protocol

As we focused on occipital lobes in SSVEP experiment, we thought about dealing with minimum number of electrodes to have maximum flexibility. So, EEG signals are also acquired by OpenBCI kit from P3, P4, O1 and O2 channels. In this experiment, the training scenario was performed by the first four previous participants. The experiment protocol is proposed to be a descriptive scenario of daily life attitudes. Each subject was trained by one session containing 8 trials of each of the three simulated states: **(1)** drowsiness state simulated by a closed-eye trial without any thinking task, **(2)** relaxation state simulated by a resting seat trial without task execution, and **(3)** alert state simulated by calculation problem task for some equations written randomly. Each trial is recorded during 60 seconds to make sure that the user is deeply integrated into the state. The inter-trials duration is set to 60 seconds to be able to successfully switch between two states.

B. Proposed processing method

The same preprocessing and classification algorithms as previous methods are used. The difference is in the feature extraction stage, where different possible drowsiness features are studied and compared. First, relative energies of five sub-signals can be extracted from the signal: delta, theta, alpha, beta and gamma as they have been proven to be drowsiness biomarkers in many studies [12], [13]. After extraction, their relative energies are calculated. The extraction of these sub-signals was done by a comparative study between **(1)** filtering where corresponding filters are designed in MATLAB (delta is designed with low-pass filter with upper-frequency of 3, the

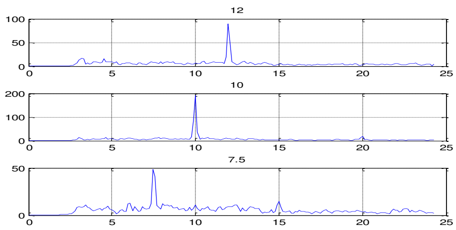

Fig. 2. Power Spectral Density by PWLECH for Subject 2 at her optimal channel O1 for the three frequencies

TABLE I. ACCURACY (%) FOR EACH SUBJECT AND THEIR CORRESPONDING SINGLE OPTIMAL CHANNEL USED IN ONLINE TESTING

Accuracy	*Oz*	*O1*	*O2*	*Optimal Channel*
Subject 1	**87.5**	**87.5**	86.4583	**Oz-O1**
Subject 2	81.25	**91.67**	79.1667	**O1**
Subject 3	36.4583	**90.625**	64.5833	**O1**
Subject 4	**86.4583**	78.125	77.083	**Oz**
Subject 5	65.625	**89.58**	87.5	**O1**

others with band-pass filters of [3-7] for theta, [7-14] for alpha, [14-40] for beta and [40-60] for gamma), **(2)** filtering with overlapping where the 60 seconds signal trial is divided into 10 seconds signals with 50% overlapping, **(3)** DWT with 6-level decomposition. Second, spectral, approximate and sample entropies are calculated from the power spectral density (PSD) plot using PWelch method [14]. Third, statistical parameters including mean, standard deviation, skewness and kurtosis are calculated from the PSD. Finally, frequency-related parameter including power, mean frequency, median frequency and peak frequency of PSD are computed.

C. Results

From the power spectrums for the three states at each channel, differences in the delta, theta, alpha, beta and gamma are noticed and thus their relative energy are computed and the result is shown using the filtering method with overlapping in Figure 3. Variations of each frequency band energy emphasis the theory where high frequencies are dominant when the user is focused while lower frequencies are integrated when the user is in a meditation and more in a sleepy state. And from these accuracy results shown in Table II., it is seen that entropy features cannot be applied in this experiment while relative energies using band-pass with overlap and the frequency related features can be good indicators of physiological state.

V. COLOR DETECTION

A. Experiment protocol

EEG signals are measured from O1 and O2 channels using OpenBCI. The training scenario was performed by the first three previous participants. Each subject was sitting in a black room and trained by two session as described in Figure 4.

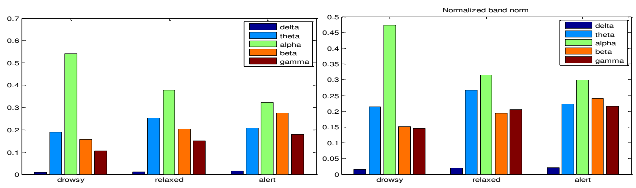

Fig. 3. Histogram of relative energy distribution of frequency bands in O1 (left) and O2 (right) for the three physiological states

TABLE II. ACCURACY (%) OF THE SIX APPROACHES FOR EACH SUBJECT

Accuracy (%)	Relative energies			Entropy	Statistical	Frequency related
	Wavelet	*Filter*	*Filter & overlap*			
Subject 1	85.415	79.165	85.418	66.670	81.2485	83.330
Subject 2	74.995	70.835	75	58.335	77.0835	83.330
Subject 3	60	70.835	81.250	58.335	66.670	75
Subject 4	83.33	70.835	79.165	62.5	66.67	75

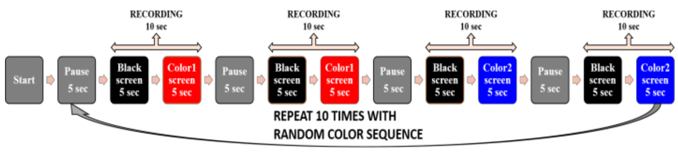

Fig. 4. Color experiment protocol description for a session

B. Proposed processing method

Similarly, the difference is in the feature extraction stage, where time-frequency domain parameters were studied because of color's influence in both time and frequency domain where it is found that that higher low frequency power and smaller latency are observed for red color rather than for the blue one [15]. Three methods were compared: **(1)** Event-Related Spectral Perturbation (ERSP); calculated using FFT method at the time between 1 second before color stimulus and 2 seconds after, and at each frequency lower than 30Hz. **(2)** Short-Time Fourier Transform (STFT); where time signal is divided into shorter segments of equal length with Fourier transform calculated and averaged. **(3)** Discrete Wavelet Transform (DWT) with db8 wavelet and 6-level decomposition.

C. Results

As observed in Figure 5. In time domain, the latency of detecting red color is smaller than blue because red directly increases the alpha power after the color stimulus while the latency of the blue one is about 500ms. In frequency domain, the alpha band between 400ms and 700ms is higher in red color. And for beta band, the blue color shows a decreased power between 500ms and 1000ms, in opposite to the red color. These results are compatible with theory and other researches on the ERSP for color stimulation. In a similar way, we tested the accuracy of other time-frequency features as DWT and STFT. The results are shown in the table III.

VI. Discussion and Conclusions

In this work, three powerful methods were projected into robotics and smart home domains. After acquiring the data offline and performing the training, many algorithms were implemented for processing and compared to choose the optimal ones. Then, in the online testing part, the user uses his own built classifier to choose between two options by a red and blue color detection that does not require any effort. Then he can control a robotic arm to feed himself from two different plates using SSVEP that offers high performance with minimal training time. Also, he is able to live in a brain controlled home where he can change the lighting intensity and ventilation speed voluntary by SSVEP or automatically depending on his drowsiness level using NodeMCU.

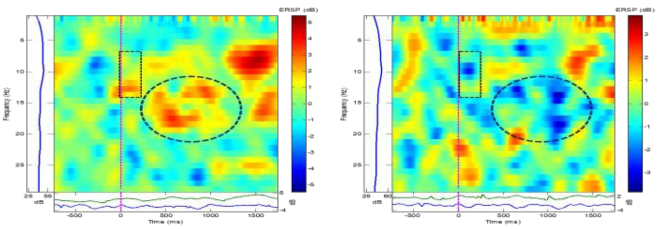

Fig. 5. ERSP for subject 1 at O1; for RED (left) and BLUE (right) colors

TABLE III. Accuracy (%) of the studied methods for each subject

Accuracy (%)	*ERSP*	*STFT*	*DWT*
Subject 1	98.75	67.5	81.25
Subject 2	53.75	55	93.75
Subject 3	62.5	50	90

This work presents many advantages. For the SSVEP, it has successfully used only one channel to classify the frequencies which makes it practical, with small number of training that doesn't need to be updated, and showed good accuracy in online testing even when the lights are on. For the physiological state, it has also used only four channels which is a small number compared to other research studies. And an important point is the capability of 3-class classification (drowsiness, meditation and alertness) not only binary classification as in most studies. As a future work, the hardware may be reduced to only four EEG sensors with the same microprocessor and the training dataset can be increased to generalize the results. Hoping finally to translate this BCI system to a real commercial system than can be used to benefit the human kind.

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