EEG-Based Brain-Controlled Wheelchair with Four Different Stimuli Frequencies

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***Abstract*—The paper considers a non-invasive brain computer interface uses EEG-SSVEP signals over visual cortex to control electronic wheelchair movement (i.e., forward, backward, left, and right). The main goal of the paper is to help people with severe motor disabilities (i.e., spinal cord injuries) and to provide them with a new way of communication and control options. In this paper, offline analysis of the data collected is used to make the user able of controlling the movement of the electronic wheelchair. The data are collected during a session in which four subjects with age about 25±1 years were tested. The adaptive-network based fuzzy inference system algorithm is then applied for the classification method with some parameters. In the offline analysis, the implemented method shows a significant performance in the classification accuracy level and it gives an accuracy level of more than 90%. This result suggests that using the adaptive-network based fuzzy inference system algorithm can improve real time operation of the current BCI system.**

***Index Terms*—Neural Networks, ANFIS, Feature extraction, Classification, EEG-SSVEP, BCI.**

I. Introduction

The human brain has an intensive chemical and electrical activity called biosignals which occur at specific times and at well-localized brain sites. All of that is observable with a certain level of repeatability under well-defined environmental conditions. These simple physiological issues can lead to the development of new communication systems. Detecting and analysing biosignals of the human brain could be beneficial for us to figure out the brain construction and operational function. The application of brain signals detection also was developed in various fields. Steady state visual evoked potential (SSVEP) is one of the important biosignals of the brain which has a wide application in examining brain activity and cognitive functions [1]. These signals are natural responses for visual stimulations at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates an electrical activity at the same (or multiples of the) frequency of the visual stimulus. They are used for understanding which stimulus the subject is looking at in case of stimuli with different flashing frequency [2, 3].

The electroencephalogram based steady state visual evoked potential (EEG-SSVEP) has become a valuable tool for the measurement of cognitive function in medical and research applications. Numerous applications of EEG based event related potential such as P300 and SSVEP are as a communication tool by people with neuromuscular disorders (such as BCI spellers, BCI wheel-chair) [1, 4-12], as a audio speller [13], and a lie detector [14]. Recently, a great variety of its potential applications has been widely studied such as smart homes, internet browsing, market researchers, BCI for controlling hand grasp [15], its correlation with the memory status of patients with mild cognitive impairment. Previous research has shown that several aspects of the ERP (especially latency, magnitude, and topography) are highly variable across trials. Many techniques appeared in research area to resolve the problems of EEG (specifically for obtaining maximum amplitude of SSVEP) are not sufficiently standardized especially for clinical usage.

In this paper, offline maximum amplitude of SSVEP feature extraction using ANFIS is proposed. A modular classification ANFIS algorithm based on two techniques in updating parameters is used. To fine-tune parameters that indicate membership functions (MFs), ANFIS uses gradient descent method. To identify the coefficients of each output equations, ANFIS uses the least-squares method. This approach is called hybrid learning method since it combines gradient descent and the least-squares methods [16]. In order to model complex nonlinear systems, the ANFIS model carries out input space partitioning that splits the input space into many local regions from which simple local models (linear functions or even adjustable coefficients) are employed [16][17][18].

The performances of any BCI systems are influenced by the performance of the classifications. The experimental results in this paper show that the implementation of the proposed method achieves significant statistical improvement in extracting and classifying the peak of amplitude which helps to improve different BCI applications. This result is important in order to help the people and to provide them with efficient solutions in using a BCI system.

The structure of this paper is in the following. Section 2 presents the data acquisition, feature extraction, and classification. Section 3 provides the application of the online maximum amplitude extraction. Section 4 shows the

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discussions of the experimental results. Section 5 draws conclusions.

II. METHOD

A. Data Aquisition

In the experiment, four undergraduate students (male, age 24 ± 1 years, none of whom had any known neurological deficits) were participated. A four-choice signal paradigm with different frequencies (i.e., from 6 to 9 Hz for left, right, bottom, and top, respectively) was used to stimulate the four subjects. The subjects were asked to concentrate on directed stimulus on the screen while imagining a wheelchair moving in the direction of the flashed signal. Fig. 1 and Fig. 2 indicate the experiment setup and the electronic wheelchair communication design, respectively. The EEG signals were recorded continuously using three electrodes (channels) at O1, O2, and Pz by following the 10-20 International System and digitized at a 500 Hz sampling rate (see Fig. 3). The raw data were amplified and transmitted to the computer as BCI (preprocessing, extaction, and classification) through RS232 port. The extracted signals were transmitted from RS232 port to the microcontroller as the controller to run the electric wheelchair. Each subject recorded four sessions to indicate four different directions.

B. Signal Processing

Preparatory to an analysis of the features of maximum amplitude from EEG-SSVEP signals in off-line, actual signals were recorded in three channels (O1, O2, and Pz) configuration. The raw data (Fig. 4) were first pre-processed using a sixth-order band-pass filter (BPF) with cut-off frequencies of 4 Hz and 30 Hz, respectively, see Fig. 5. These cut-off frequencies were chosen according to the EEG-SSVEP frequency about 2 to 70 Hz. It can be seen that the signals were corrupted by noises.

In order to classify the trial of EEG-SSVEP signals when the subjects focus a four-choice signal paradigm with different frequencies (i.e., from 6 to 9 Hz for left, right, bottom, and top, respectively), the ANFIS method is applied. In a fuzzy inference system, there are three types of input space partitioning: grid, tree, and cattering partitioning. The "curse of dimensionality" refers to such situation where the number of fuzzy rules increases exponentially with the number of input variables [16][19]. The number of features in the ANFIS classifier is represented by the number of the input data, however only few of them are relevant the predicted class. To avoid the presence of large number of weakly relevant and redundant features; this is usually attributed to the fact that irrelevant features decrease the signal-to-noise ratio [16].

ANFIS's network organizes two parts like fuzzy systems. The first part is the antecedent part and the second part is the conclusion part, which are connected to each other by rules in network form. The network structure of ANFIS can be described as a multi-layered neural network as shown in Fig. 1. Where, the first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions (MFs), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of layer fourth. Here for ANFIS structure and the classification scheme, as shown in Fig. 6 and Fig. 7, two inputs and two

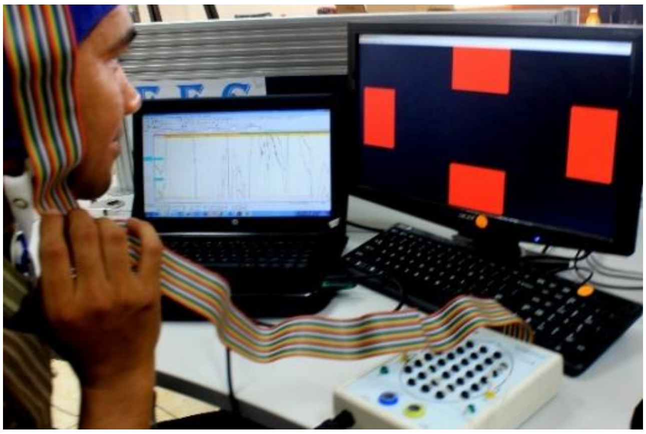

Fig. 1. An experiment setup of EEG recording

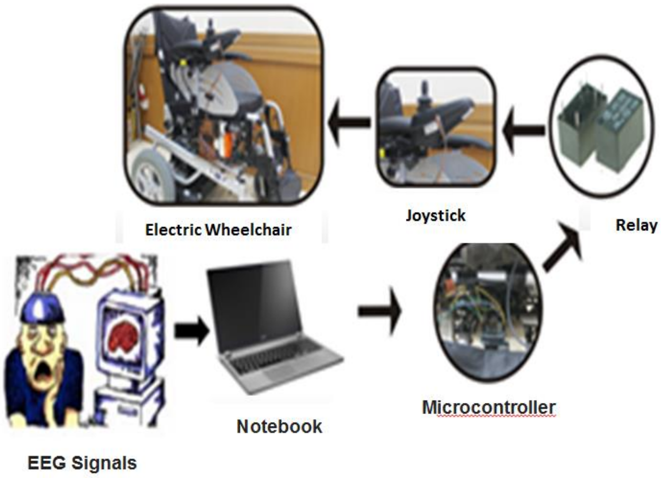

Fig. 2. Electric Wheelchair System with RS232 communication

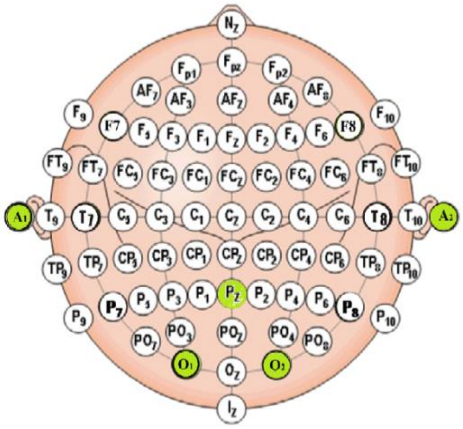

Fig. 3. Electrodes position used in the experiment.

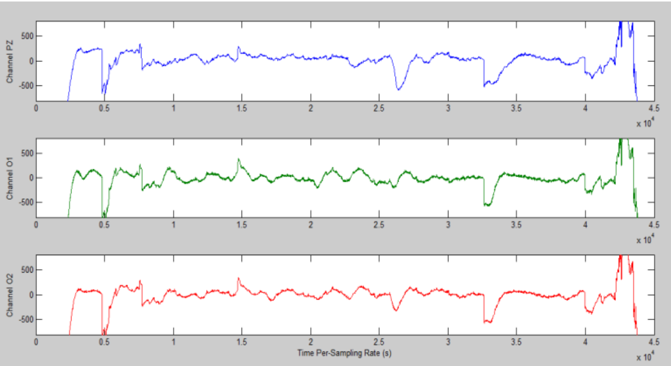

Fig. 4. RAW Data of EEG-SSVEP

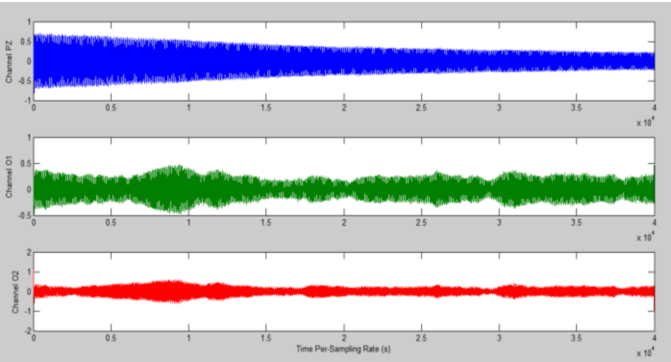

Fig. 5. Filtered EEG-SSVEP

labels for each input are considered. The feed forward equations of ANFIS are as follow:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$) (1)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$) (2)

where A_1 and A_1 are a fuzzy set in x; B_1 and B_2 in y. A_i and B_i (i=1,2) are the fuzzy variables characterized by fuzzy membership functions and f_i is a real constant value. The output of each layer can be represented by:

$$O_i^1 = \mu A_i(x) \; i = 1,2 \tag{3}$$

$$O_i^1 = \mu B_{i-2}(y) \; i = 3,4 \tag{4}$$

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \tag{5}$$

where

$$\mu_{Ai}(x) = \frac{1}{1+\left\{\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}} \tag{6}$$

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{7}$$

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{8}$$

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{9}$$

with hybrid Learning algorithm as

$$f = \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 \tag{10}$$

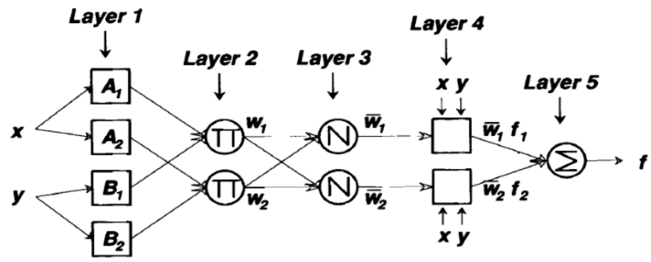

Fig. 6. ANFIS architecture

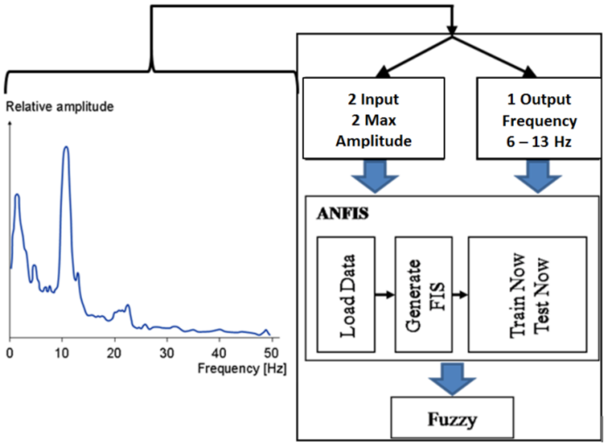

Fig. 7. Data train development of ANFIS for Classification

III. Experimental Results

Since the desired maximum amplitude signal to the EEG power (noise) ratio is small, a method of extracting and classifying the desired signal from the EEG is desirable. One way of gaining further insights into EEG signals is by applying ANFIS classifier. The features were extracted every 320 (one trial) for about 16 target trials. Although there are some noticeable improvements, it remains difficult to identify the associated signals with respect to the given stimulus.

The training data set of ANFIS is given in Fig. 6. The extracted maximum amplitude with its frequency ranges about 6 to 10 Hz is given in Fig. 6. Table 1 indicates the comparative frequencies for all subjects of each peak (channel O1). The bold frequencies indicate that the obtained result are different with the given stimulus. Those errors normally coused by human error in the experiment. The similar results also obtained with the other channels which indicate that the enhancement of the extracted amplitudes with the proposed method can be achieved. To verify the accuracy of the extracted signals, each signals for all subject is classified by using the ANFIS method. The classification result with average about 90% accuracy is obtained.

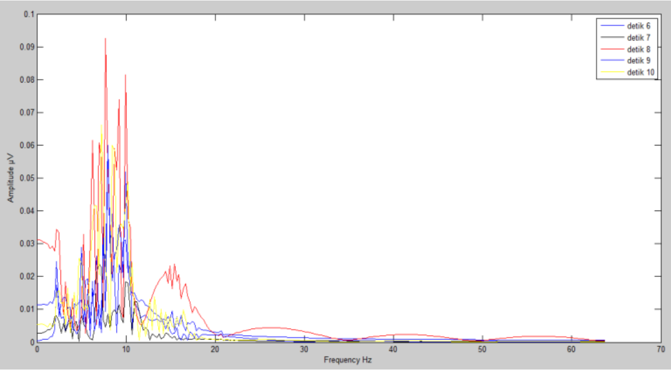

Fig. 8. Maximum Amplitude of Channel O1

TABLE 1
AVERAGE EXTRACTED FREQUENCIES BASED ON GIVEN STIMULUS AT THE MAXIMUM AMPLITUDE

No	**Stimulus**	**Frequency (Hz)**			
		S1	**S2**	**S3**	**S4**
1	**Left**	6,308	6,475	6,475	6,724
2	**Top**	9,463	9,131	9,131	9,048
3	**Right**	**8,384**	7,637	7,637	**8,301**
4	**Bottom**	8,218	8,384	8,384	8,052
5	**Left**	**8,052**	**7,969**	**7,969**	**7,388**
6	**Top**	9,214	9,629	9,629	9,048
7	**Right**	**8,301**	**8,301**	**8,218**	7,305
8	**Bottom**	8,301	8,218	8,218	8,301

IV. Conclusions

A non-invasive brain computer interface used EEG-SSVEP signals over visual cortex to control electronic wheelchair movement (i.e. forward, backward, left, and right) was developed. The developed ANFIS method applied at the classification step had the advantage of much less training time and provided a significant performance in the classification accuracy level. The proposed method gave an accuracy level of more than 90%. This result suggested that using the adaptive-network based fuzzy inference system algorithm improved the real time operation of the current BCI system.

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