A P300-Based Brain Computer Interface for Smart Home Interaction through an ANFIS ensemble

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***Abstract*—Adaptive neuro fuzzy inference systems (ANFIS) has been applied in brain computer interfaces (BCI) in different ways such as mapping of P300 or fusing information from EEG channels and it has reached high classification accuracy.This work proposes a combination of ANFIS classifiers by voting for a single-trial detection of a P300 wave in a BCI, using four channels; five healthy subjects and three post-stroke patients have participated in this study, each participant performs 4 BCI sessions, crossvalidation is applied to evaluate the classifier performance. The results of average accuracy were greater than 75% for all subjects, similar results were gotten for healthy subjects and post-stroke patients, but the better classifiers for each subject have achieved accuracies greater than 80%.**

***Keywords*—P300, brain computer interface, ANFIS.**

I. Introduction

Brain-Computer Interface (BCI) is a system that enables to the subject or patient to communicate or control devices through brain activity [1], BCI are implemented using different paradigms, such as are motor imagery (MI), evoked potential P300, and cognitive tasks [2]. One application of P300 paradigm is the speller, that is used as an alternative forms of communication; specifically, for patients with Amyotrophic Lateral Sclerosis (ALS) [3], [4]. Farwell and Donchin proposed the first categorized Row-Column Speller, in which the users see a 6x6 characters matrix [5]. Posterior investigations are based on this approach, they enhance the character presentation mode but keeping the matrix presentation [6], [7]. The speller paradigms was enhance with the development of region-based paradigm [8], [9], such as Hex-o-Spell [10] and Cake Speller [11]. In these paradigms, the character selection is performed in two steps: first, the subject has selected a region that is composed of set symbols and second, region is expanded for character selection.

These approaches (except Cake Speller) were developed under the assumption that the result of the paradigm is minimally dependent on visual evoked potentials (VEP) other than P300. It has been demonstrated in [12], [13], and [14] that the precision of the Speller depends on the user attention to the target. This fact limits its practical scope to patients with oculomotor control affection. On the other hand, the Speller methods achieved less precision than Eyetracking, so this fact discourages practical applications [15].

For this reason, visual P300 have been used in order to build a BCI; in auditory or tactile approaches require a greater training of the patient to learn the correspondence between the stimulus and the symbol [11]. In addition, the precision obtained by visual P300 is superior to the other modalities [16].

Machine learning algorithms are used in P300 applications, such as support vector machine (SVM) ensemble in [17] and [18], where seventeen and two healthy subjects used a Row-Column Speller 6x6 and the authors achieved a score classification greater than 92% respectively.In [19], they used SVM and a modification of Speller 6x6 to Speller 4x10 so as to classify the visual evoked potential. This work used six healthy subjects and reported classification results of 75%. In [20], the authors used Stepwise linear discriminant analysis (SWLDA) in Speller 6x6 for eight healthy subjects. This work reported classification results 92%. An Hidden Markov Models (HMM) was proposed to classify EEG data from Speller 6x6 in [21]. This work reported classification results of 85% offline and 92.3% online.

Hoffman [22] developed an application about selection from six figures to validate its algorithm of detection of P300. The protocol used is based on oddball paradigm, consisting of six images: television, telephone, lamp, door, window and radio; these images were flashed randomly, one at time. In [22] the authors use Bayesian linear discriminant analysis (BLDA) and Fisher linear discriminant analysis (FLDA) to classify the visual P300, the correct classification score reached 90% and 80% respectively. This approach can be used to select control options into a Smart Home application.

About Smart Homes using BCI, in [23] nine subjects used a 6x6 Character-Speller and Icon-Speller in order to compare and analyze their performance. This work reported that Character-Speller outperformed Icon-Speller with 80% and 50% of average accuracy respectively. For Virtual Reality Environments, in [24] twelve subjects used different Speller masks (i.e. music, tv channels, etc) to control a smart home application. These results reported score classification of 75%. Furthermore, in [25] one subject with Amyotrophic Lateral Sclerosis (ALS) used a 6x6 row-column Speller to control a television. The classification accuracy displays 83% with SWLDA classifier.

Adaptive neuro fuzzy inference system (ANFIS) has been used in BCI with considerable results [26]. In [27], eight subjects are stimulated by an application that shows in a screen one starship to be controlled by P300 occurrence, where an ANFIS classifier is applied to map the P300 signal to a triangle pulse for an easy P300 detection; it got an accuracy of 85%. Fuzzy approach to fuse information from different electrodes to improve the P300 detection [28], this work reached an score classification greater than 87%. Furthermore, ANFIS classifier was used to control a robot arm by motor imagery [29], using 4 commands and eleven healthy subjects participated in this experiment. The results reported an accuracy greater than 65% in its classification.

This work presents a P300-based BCI, it is based on Hoffman approach [22], the same six figures were used like stimulus; and eight subjects have participated in this study, P300 detection is carried out through a combination of ANFIS classifiers by voting, using four EEG channels.

It is structured as follows. The experimental procedure is presented in Section II, Methods are shown in Section III. The results are presented in Section IV. Finally, in Section V, we present the conclusions.

II. Experimental Procedure

A. Participants

Eight volunteers (7 males and 1 female); aged between 20 and 55, participated in our study, where Subjects S1 to S5 are healthy and subjects S6 to S8 are post-stroke patients. In this study ethical approval was obtained from the Cayetano Heredia Peruvian University Ethics Committee and written informed consent was obtained from subjects before each procedure.

Table I. Subjects General Data

Subjects	Age	Handed	Gender	Diagnosis
S1	33	right	Male	Healthy
S2	21	right	Male	Healthy
S3	29	right	Male	Healthy
S4	20	right	Male	Healthy
S5	20	right	Male	Healthy
S6	52	right	Female	Ischemic post-stroke
S7	20	left	Male	Hemorrhagic post-stroke
S8	55	left	Male	Ischemic post-stroke

Subject S6 was able to perform normal movements, but with reduced spoken communication. Subject S7 was able to do only simple movements with reduced spoken communication. Subject S8 was able to perform normal movements, but with severe problems in spoken and hand-written communication.

All post-stroke subjects were recruited from the Cayetano Heredia Hospital.

B. Experimental setup

This work is based on Hoffmann approach [22]. Participants faced a computer screen where six images were displayed (see Fig. 1), they were placed in a 2 x 3 matrix. For this case, the system uses a black background (Fig. 2).

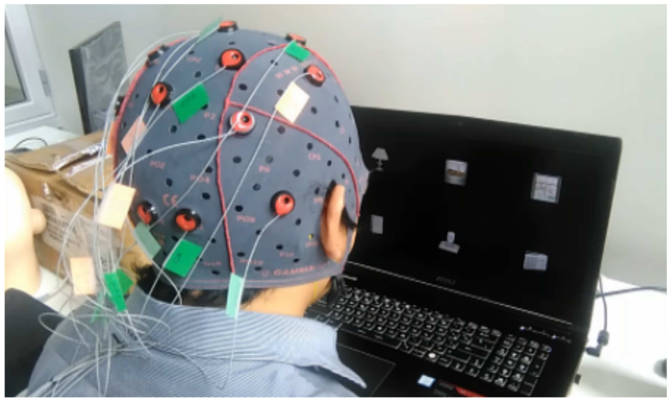

Figure 1. Subject in P300 speller experiments.

The images were flashed in random sequences, one image at a time. Each flash of an image lasted 100 ms and after it 300 ms none of the images was flashed (Fig. 3). Each image was intensified more than 20 epochs with a maximum of 25 per run of the program.

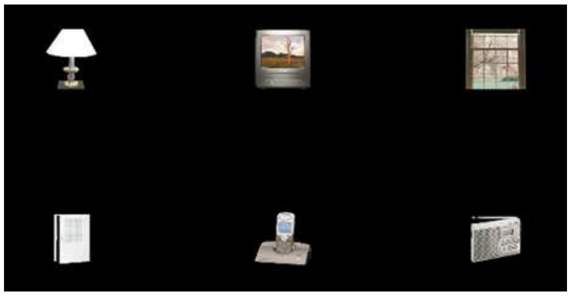

Figure 2. Display of the six images corresponding to a household objects in the smart home in the computer screen.

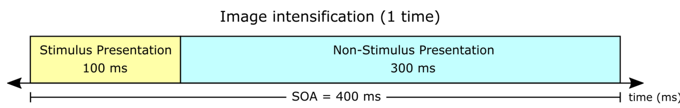

Figure 3. Timeline of each stimulus presentation.

A 16-channel electroencephalograph (EEG) system (g.USBamp, brand g.tec) is used to record brain activity.

The system was developed, offline and online modes, using OpenCV libraries in C++ programming language and Matlab R2016a (http://www.mathworks.com/) using a Intel(R) Core(TM) i7-4710HQ CPU @ 2.50GHz - RAM 16 GB - 64 bits OS.

C. Training session

Each subject performs four offline sessions for training. Offline sessions were separated in two per day. Two sessions were separated in breaks of 8 to 10 min. A session has six runs of the program and each run was separated by breaks of 1 min. Participants were informed that they should pay attention and avoid to moving and talking during the EEG recording. The duration of one run and one session (electrodes setup and short breaks) was approximately one minute and 30 min.

III. METHODS

A. Signal Processing

1) Data acquisition: EEG signals were acquired using a 16-channel *g.tec (g.USBamp)* system. Electrodes were placed in accordance with the international 10/10 system at Fz, FC1, FC2, C3, Cz, C4, CP1, CP2, P7, P3, Pz, P4, P8, O1, O2, and O3. Electrode impedance was always kept under 5 kΩ. The ground electrode was placed at the right mastoid and the reference electrode was placed at the left earlobe. The EEG was sampled at 2400 Hz. For the offline experiment, we acquired raw data and stored in binary files for a posterior analysis.

2) Preprocessing: Before training and testing, signals were filtered using IIR zero-phase bandpass filter which cut-off frequencies were 1.0 Hz and 15.0 Hz.

Filter was a six order forward-backward Butterworth filter. Then, the EEG data was downsampled from 2400 Hz to 32 Hz.

3) Feature Extraction: For each channel, we extracted all data samples between 0 to 1000 ms posterior to the beginning of the stimulus, in this case we had 32 samples per trial.

4) Winsorizing: Eye blinks, eye movement, muscle activity, or subject movement can use large amplitude outliers in the EEG. To reduce the effects of such outliers, the data from each electrode were windsorized. For each channel, signal under the 10th percentile and above 90th percentile were replaced by the 10th percentile or the 90th percentile respectively [22].

5) Normalizing: All samples from each electrode were normalized to the interval from 0 to 1.

6) Channel Selection: The mean of EEG signals is calculated, the occurrence and not occurrence of P300 is displayed in Fig. 5; 4-channels (P7, P4, O1, O2) are chosen due to the observation of P300 and Event-Related Potential (ERP) cortical fucus. Channel selection could change depending on each subject.

B. Classification

1) Feature Vector construction: There are 4 feature vectors, each one is a downsampled EEG signal of the chosen channels. Each channel has 200 trials with 32 samples per trial. Figure 4 shows how Training Data and Testing Data were obtained per channel. It would be improved by methods based on channel energy and P300 waveforms for automatic channel selection.

2) Training: 100 trials of P300 occurrence and 100 trials of P300 not occurrence are taken, selecting 160 trials randomly for ANFIS classifier training, 5 fold crossvalidation is applied to have the mean of accuracies.

3) ANFIS Classifier: The ANFIS neural network integrates capacity of learning complex non-linear function of neural network with a basis for coping with an environment that is imprecise and uncertain based on Fuzzy inference. ANFIS is composed by 5 layers, layer 1 calculate the membership degree of an EEG trial. Layer 2 is a T-norm operator (AND) that outputs the firing strength of a rule. Layer 3 normalizes the firing strength Layer 4 produces output values resulting from the inference, it is calculated by the product of the output

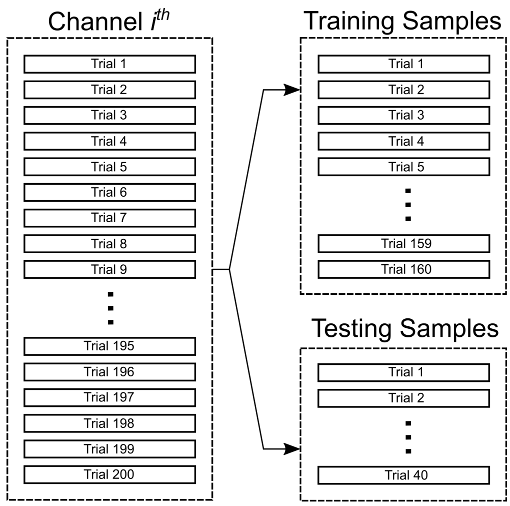

Figure 4. Training and testing data selection scheme.

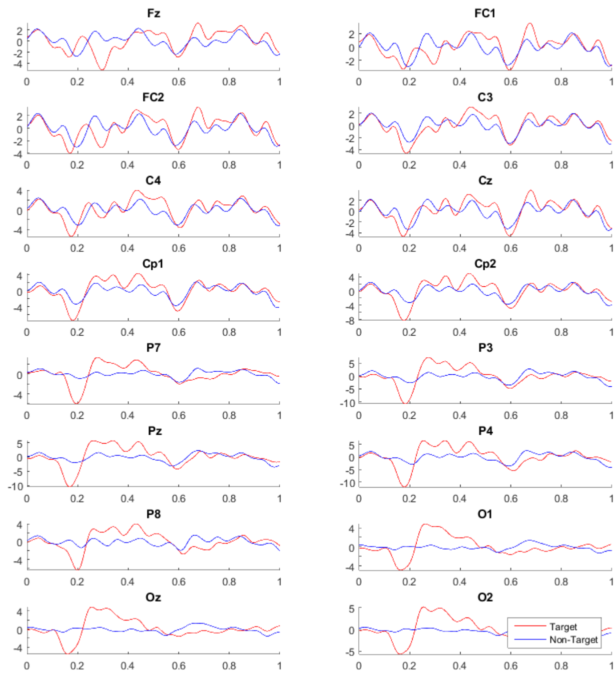

Figure 5. Average of EEG signals per channel during occurrence and not occurrence of P300.

from layer 3 and a first order polynomial. Figure 6 describes the procedure of the classification process, where D in each channel subindex is refered to downsampled.

ANFIS classifier was implemented using the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) Library for Simulink, which is available on Mathworks File Exchange [30].

ANFIS is set as binary classifier that discerns between occurrence and not occurrence of the P300 wave. ANFIS is configured as learning rate (η = 0.01) and the momentum (α = 0.002), the number of inputs is 32 and 1 output. An ensemble of 4 ANFIS Classifiers are trained, one per channel; the 4 outputs are compared, the classifier decision is performed by voting.

If two or more classifiers show the occurrence of P300 signal, then the ensemble classifier decision will show a possitive occurrence of the P300.

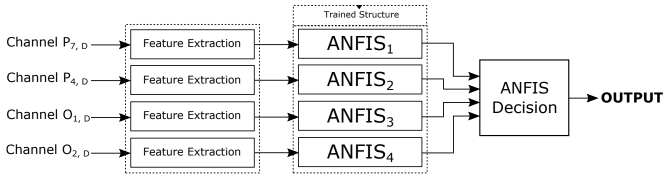

Figure 6. ANFIS ensemble classifier structure.

IV. RESULTS

In Table I, it can be observed the results of five fold cross-validation for eight subjects by 4 sessions, accuracies (Acc) and F1-scores (F1) are shown. On average the subjects S1 and S4 had the better performances, their accuracies and F1-scores present a balanced classifier.

Healthy subjects S2, S3, and S5 had a similar performance to patients S6 and S8; although patient S7 had the lower performance, this patient has the most critical condition post-stroke.

Table II. CROSSVALIDATION OF ANFIS CLASSIFIERS, ACCURACY AND F1-SCORE BY SESSION

Subj.	Session 1		Session 2		Session 3		Session 5	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
S1	84.0	83.4	92.0	92.2	80.0	81.1	85.9	85.8
S2	77.5	77.4	82.0	81.2	76.0	74.6	74.0	72.5
S3	72.5	72.7	64.0	64.0	78.0	78.7	75.0	74.1
S4	80.0	80.1	83.0	83.2	79.0	78.1	75.0	75.4
S5	77.5	78.1	85.0	84.9	77.5	79.1	78.0	78.1
S6	79.0	78.5	78.0	78.9	70.5	70.7	72.0	71.7
S7	73.5	72.7	68.5	67.9	73.0	72.8	65.5	64.4
S8	78.0	78.7	78.0	76.5	79.5	79.7	78.0	77.5

The performances of the best trained ANFIS classifiers for each subject are shown in Table II, the subject S1 presents the best performance of all subjects; but the following best performance belongs to the subject S5, and the subject S8 had a similar performance to the subject S5.

Table III. BEST ANFIS CLASSIFIERS, ACCURACY AND F1-SCORE

Data	Subjects							
	S1	S2	S3	S4	S5	S6	S7	S8
Acc.	97.0	90.0	85.0	90.0	95.0	87.5	80.0	95.0
F1	97.6	90.5	84.2	88.9	95.0	87.8	80.9	94.7

It is noticed that patient S7 had the lower performance in average (Table I) but its best ANFIS Classifier got an accuracy of 80% and F1-score of 80.9%. This performance is lower compared with other subjects yet, but it can be used in a P300-based BCI due to it is greater than 80%. Best ANFIS classifiers will be implemented using Hoffmann approach. In comparison with ANFIS applications to detect P300 waveforms [27], [28], [29], our proposed approach got better results, it achieved accuracies greater than 90% in the most cases, see Table II.

V. CONCLUSION

The detection of P300 occurrence using combination of four ANFIS classifiers by voting has obtained significant results for healthy subjects and post-stroke patients.

The performance of this P300-based BCI depends on the patient situation; i.e., damage degree in central nervous system and affected brain regions by stroke. Even though, several training sessions provide a suitable trained classifier, and crossvalidation is useful to find it. A patient critical condition can be compensated by a longer training time.

In future works, we will extend the methodology of this work by employing more complex fuzzy learning system that able to cope with higher levels of uncertainty and adaptability [31].

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