A PROPOSED METHOD FOR INCREASE ACCURACY OF CLASSIFICATION P300 SPELLER

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Abstract: *A P300 speller is one of applications the brain computer interface (BCI), introduced by Farwell and Donchin in 1988 [1]. In this paper proposed a new method for increase the accuracy of classification P300 speller. Uses a dataset for (16) healthy subjects. The new method including is feature extraction using Principle Component Analysis (PCA), and the classification using Support Vector Machine Linear (SVML). As it was calculated performance and activity of each electrode whether correlated or uncorrelated of speller task. Show that the proposed method is accurate and efficient.*

Keywords: *Brain Computer Interface (BCI), P300 speller, Accuracy of classification P300.*
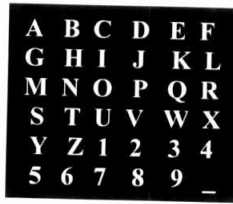
1. Introduction

A brain-computer interface (BCI) sometimes called a mind-machine interface (MMI), direct neural interface (DNI), synthetic telepathy interface (STI) or a brain–machine interface (BMI), is a system that connects the brain to a computer or any other devices directly and avoids the need for peripheral nerve and muscle activities to execute user's actions, measured by brain activity [2]. The main objective of BCI research is to allow patients with severe motor disabilities to communicate and the ability to control [3].

The challenges of BCI to the highly difficult and complex, noisy, and changes normal of brain signals, chiefly with non-invasive recordings using scalp EEG, in sometimes the computer or other devices misinterprets the brain signals and makes a choice that does not match with user's intention [4].

1.1. P300 Speller:

Is a model developed to restore communication in locked-in patients [5]. Signal's P300 is an EEG positive deflection that happens approximately 300 ms after stimulus and is recorded by centro-parietal passive EEG sensors [6]. Using to select items displayed on a computer screen [7]. All items are displayed and the user focuses his attention (and gaze) onto the target item. Groups of items are successively and random repeatedly flashed, but only the group that contains the target item wills a P300 response. [8].

This interface is a 6x6 matrix that is displayed on the screen, made up of 26 letters of the alphabet, nine numbers and a symbol that enables the cancellation of the previous selection, allows the user to write a text on the computer screen, shown P300 speller in Figure 1 [5].

Figure 1: P300 speller matrix [5]

1.2. Related work:

In 2012 Perrin Margaux, et al., [8], proposed implemented a P300, including error detection, data recorded in 16 healthy volunteers. Whenever an error was detected, a new decision was made based on the second best guess of a probabilistic classifier. Used mixture of multi-dimensional Gaussian model as a classifier. Deepesh Kumar [9], in 2013, proposed detect the P300 wave. Used discrete wavelet transforms (DWT) for feature extraction of EEG signal, for two subjects. Principal component analysis (PCA) technique used for reduction of the dimension of the feature, and classification used support vector machine (SVM) and artificial neural network (ANN), the results of the proposed method with SVM classifier better performance compared to the method with ANN. In 2014 Benjamin Blankertz et al., [10], proposed a pattern recognition method that allows for a robust single trial detection of this error potential from multichannel EEG signals, by designing classifiers that are capable of bounding false positives, which would classify correct responses as errors, this method provides a substantial improvement over the choice of a simple amplitude threshold criterion, as it had used for single trial detection of error potentials, Vanitha Narayan et al., [11], in 2015, proposed a classification algorithm for P300. Brain Computer Interface (BCI) with P300 speller helps Amyotrophic Lateral Sclerosis (ALS) patients to spell words with the help of their brain signal activities. The proposed model can be used to restore basic communicating ability for Amyotrophic Lateral Sclerosis (ALS) patients in a reliable and fast way.

2. Overview:

This paper is organised as follows: section 2 is background on BCI, P300 speller and related work, and section 3 the Architecture of BCI systems. Section 4 the proposed method, section 5 the results and discussion, and section 6 future work and conclusion the paper.

3. Architecture of BCI systems:

BCI is a brand new branch of pattern recognition. The general architecture of BCI systems is shown in Figure 2 [12].

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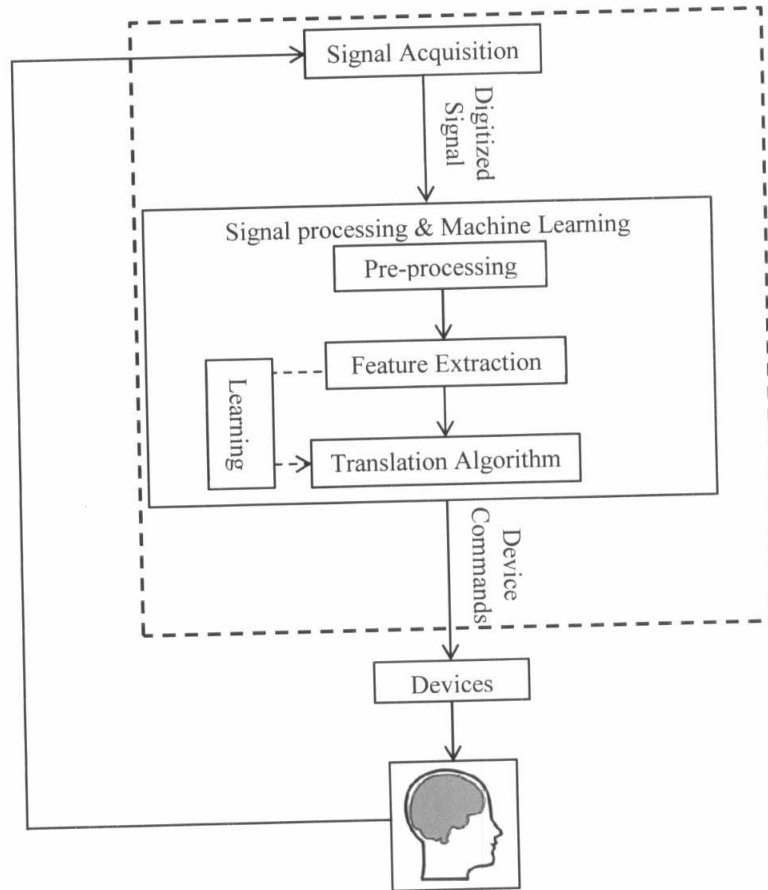
Figure 2: Architecture of BCI systems [12]

4. The proposed method: including four phases, shown in Figure 3.
4.1. Data description:

In this paper uses dataset (offline) from web site https://www.kaggle.com/c/inria-bci-challenge/data, the following data description:
The dataset recorded for sixteen healthy (16 subjects) in the study, (mean age=28.2, range 20-37), brain activity was recorded with 56 passive EEG sensors its: (Fp1, Fp2, AF7, AF3, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8, FT7, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FT8, T7, C5, C3, C1, Cz, C2, C4, C6, T8, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, POz, P08, O1, O2), whose placement followed the extended 10-20 system, Eye movements are detected by Electrooculography EOG (1 channel) derivation.

EEG samples recorded from the (56) passive called it's the same sensors (such as: Fp1 EEG samples recorded from Fp1) and other.

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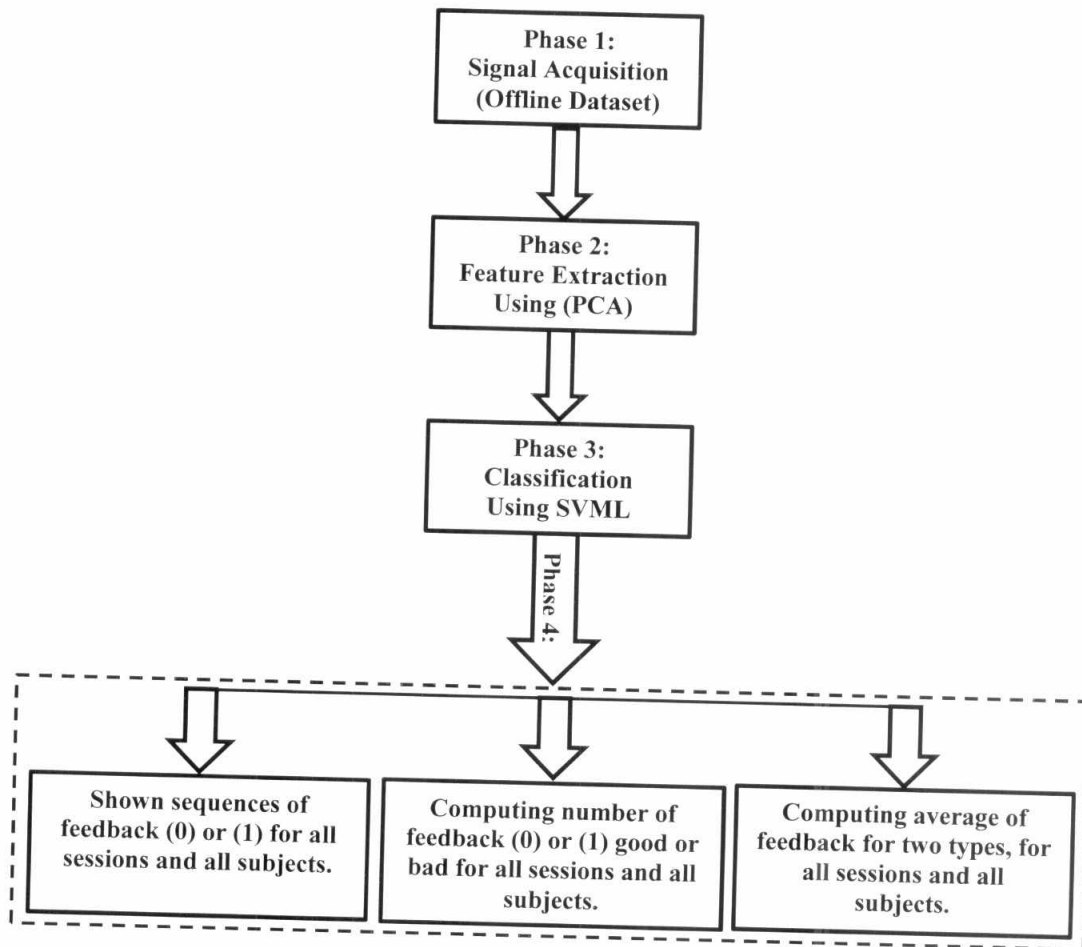
Figure 3: The proposed method

For subject who had gone through (5) sessions, (60) feedbacks were provided in each session except the fifth (last session) one for which (100) feedbacks were provided.

The subjects had to go through five copy spelling sessions. Each session consisted of twelve 5-letter words, except the fifth which consisted of twenty 5-letter words.

4.2. Feature extraction:

In this stage, using Principle Component Analysis (PCA) is a statistical features extraction method that uses a linear transformation to convert a set of observations possibly correlated into a set of uncorrelated variables called principal components. Linear transformation generates a set of components from the input data, sorted according to their variance in such a way that the first principal component has the highest possible variance. This variance allows PCA to separate the brain signal into different components.

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Used (PCA) on the Dataset, for feature extraction based on percentage for bad and good feedback, the percentage for good feedback (in.side mean to target), the percentage for bad feedback (out.side mean to out target) for all sessions and all subjects, (340) feedback for each session (240 feedback for the first four sessions, 100 feedback for fifth (last) session)), Bad feedback (negative or 0) is when the selected item is different from the expected item. Good feedback (positive or 1) is when the selected item is similar to the expected item.

The following equation computing the percentages for bad or good feedback:

$$\frac{N}{60} = \frac{X}{100}$$
$$N * 100 = X * 60$$
$$X = \frac{N * 100}{60} \qquad (1)$$

Where N (number of feedback whether good 1 or bad 0 for the first four sessions), X (the percentage of feedback for two types), as for the fifth session (last), it was a (100) feedback and this is calculated ratio percentage directly.

During a P-300 trial users are presented with letters and numbers and are tasked with spelling words. Using electroencephalogram (EEG) data the speller attempts to determine which letter the user is thinking of and presents him/her with this letter. If the letter coincides with the same letter the user was thinking about then the feedback is regarded as positive, otherwise the feedback is negative. The challenge is to predict, based on the user's response to the feedback event, whether feedback was positive (1 good) or negative (0 bad).

After error trials the error related potentials (ERP) characterized two items: negative wave denoted by (NE), positive wave denoted by (PE) [13]. After feedback whether good or bad, it's a place an event the error.

4.3. Classification:

In this stage using Support Vector Machine Linear (SVML) is a classifier constructs a hyperplane or set of hyperplanes, in order to separate the feature vectors into binary or multiclasses, such a classifier is regarded as a linear classifier, since it uses one or several hyperplanes, but in this case classification into two classes (in.side) and (out.side) based on percentage its obtained from feedback (0 or 1). And SVM calculated number of feedback whether (0 bad (negative) or 1 good (positive)) for all subjects and all sessions. Finally explain sequences of feedback for two types, for all subjects and all sessions.

The following parameters measure (the percent in the results and discussions section):

(a) Accuracy = (TP + TN)/(TP + TN + FP + FN) activity of the classifier.
(b) Sensitivity = TP/(TP + FN) the ability to errors detection properly.
(c) Specificity = TN/(TN + FP) the ability to trials detection properly.
(d) Precision=TP/(TP+FP) The percentage of good feedback (positive or 1).
TP: true positive, TN: true negative, FP: false positive, FN: false negative.

5. Results and Discussion:

The accuracy, sensitivity, specificity, and precision of classification its (90 %, 80%, 85% and 71% respectively), after applied (PCA) for feature extraction and (SVML) for classification appear the results following:

Table 1: Explain the percentage for feedback (0 and 1) for (1 & 2 of sessions).

Subjects	Session 1 for 16 subjects		Session 2 for 16 subjects	
	Out.side (%)	In.side (%)	Out.side (%)	In.side (%)
1	16.66	83.33	30	70
2	1.66	98.33	5	95
3	6.66	93.33	11.66	88.33
4	23.33	76.66	30	70
5	31.66	68.33	31.66	68.33
6	36.66	63.33	50	50
7	38.33	61.66	26.66	73.33
8	26.66	73.33	30	70
9	10	90	28.33	71.66
10	15	85	23.33	76.66
11	28.33	71.66	23.33	76.66
12	3.33	96.66	3.33	96.66
13	5	95	6.66	93.33
14	30	70	40	60
15	10	90	15	85
16	41.66	58.33	38.33	61.66
Average	20.30 ± 0.02	79.68 ± 0.02	24.58 ± 0.01	75.41 ± 0.01

The percentage for good feedback (1) present in.side (to target), the percentage for bad feedback (0) present out.side (out target), note from table (1), the percentage and average for good feedback (1) high compare with percentage and average for bad feedback (0), with an error ratio its (0.02 in session 1, 0.01 in session 2).
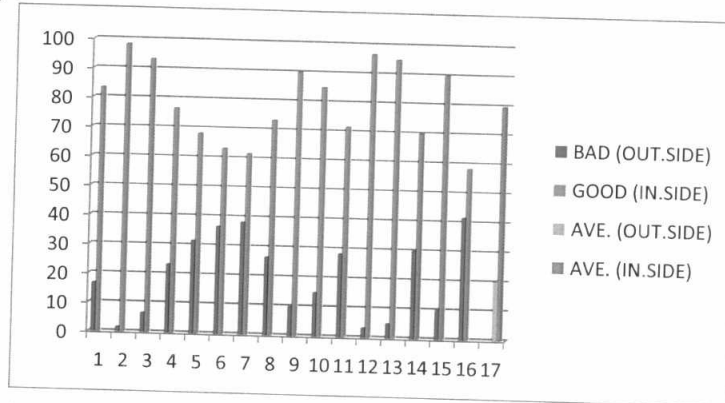
Figure 4: the chart table explains in.side, out.side, average in.side, and average out.side for session 1.

Figure 5: the chart table explains in.side, out.side, average in.side, and average out.side for session 2, note the subject (6) percentage for feedback (0 and 1) its equal.

Table 2: Explain the percentage for feedback (0 and 1) for (3 & 4 of sessions).

Subjects	Session 3 for 16 subjects		Session 4 for 16 subjects	
	Out.side (%)	In.side (%)	Out.side (%)	In.side (%)
1	40	60	41.66	58.33
2	8.33	91.66	6.66	93.33
3	5	95	11.66	88.33
4	30	70	35	65
5	45	55	45	55
6	60	40	41.66	58.33
7	30	70	30	70
8	36.66	63.33	41.66	58.33
9	40	60	43.33	56.66
10	23.33	76.66	25	75
11	30	70	31.66	68.33
12	5	95	8.33	91.66
13	10	90	8.33	91.66
14	35	65	28.33	71.66
15	23.33	76.66	38.33	61.66
16	50	50	35	65
Average	29.47 ± 0.02	70.51 ± 0.02	29.47 ± 0.02	70.51 ± 0.02

The percentage for good feedback (1) present in.side (to target), the percentage for bad feedback (0) present out.side (out target), note from table (2), the percentage and average for good feedback (1) high compare with percentage and average for bad feedback (0), with an error ratio its (0.02 in sessions 3 & 4 respectively).

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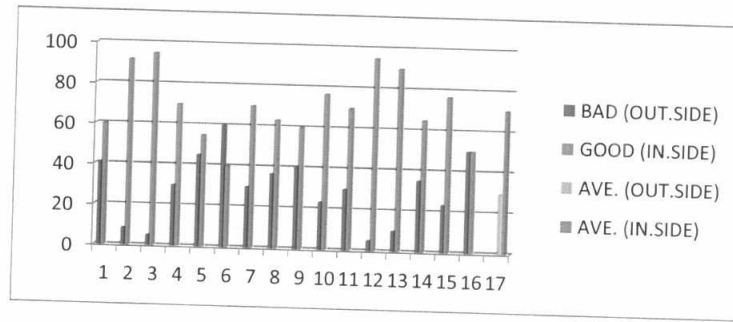
Figure 6: the chart table explains in.side, out.side, average in.side, and average out.side for session 3, note the subject (6) the percentage of b—⌐ ⌐ ⌐ ⌐ ⌐ ⌐ ⌐ ⌐ ⌐ ⌐ 1) its equal.
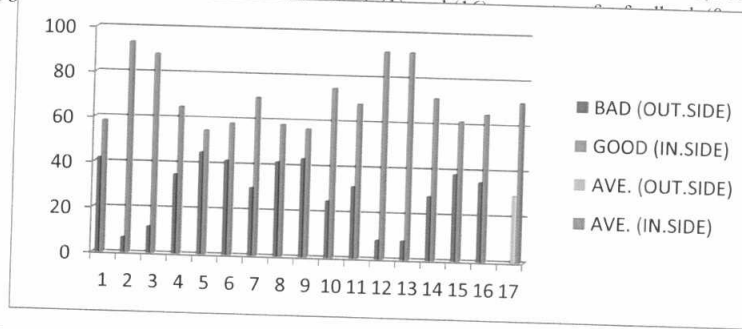
Figure 7: the chart table explains in.side, out.side, average in.side, and average out.side for session 4.

Table 3: Explain the percentage for feedback (0 and 1) for (session 5).

Subjects	Sessions 5 for 16 subjects	
	Out.side (%)	In.side (%)
1	44	56
2	11	89
3	12	88
4	44	56
5	59	41
6	50	50
7	50	50
8	47	53
9	41	59
10	27	73
11	36	64
12	15	85
13	9	91
14	39	61
15	49	51
16	60	40
Average	37.06 ± 0.01	62.93 ± 0.01

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The percentage for good feedback (1) present in.side (to target), the percentage for bad feedback (0) present out.side (out target), note from table (3), the percentage and average for good feedback (1) high compare with percentage and average for bad feedback (0)except subject (16) notes the conversely, with an error ratio its (0.01 in session 5).
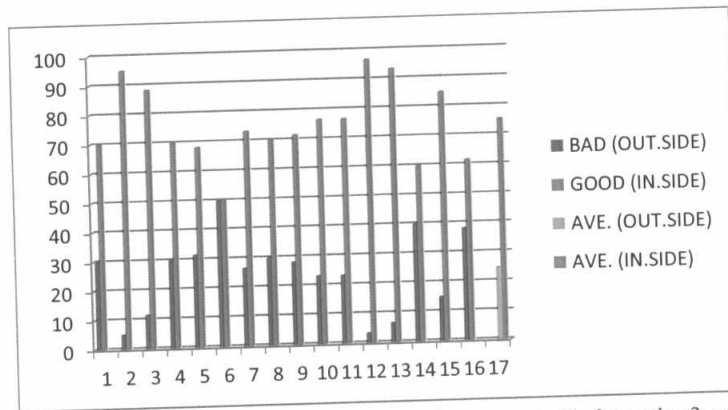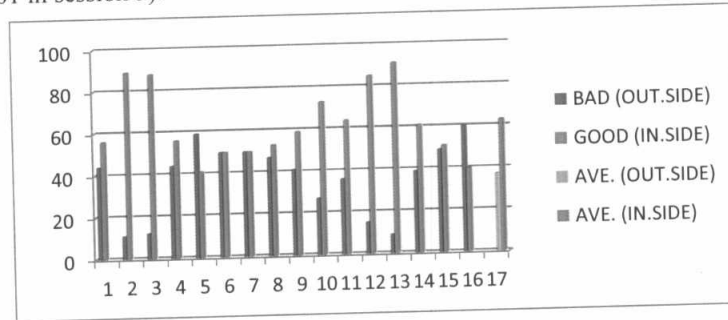

Figure 8: the chart table explains in.side, out.side, average in.side, and average out.side for session 5, note the subjects (6 & 7) percentage for feedback (0 and 1) its equal.

5.1. Performance of each electrode:

The human brain divided into several lobes its: Frontal denote is (F), Temporal denote is (T), Central denote is (C), Parietal denote is (P), and Occipital denote is (O), for each lobe specific functions. Shown Figure 9 explain the brain lobes and function of each lobe [14].
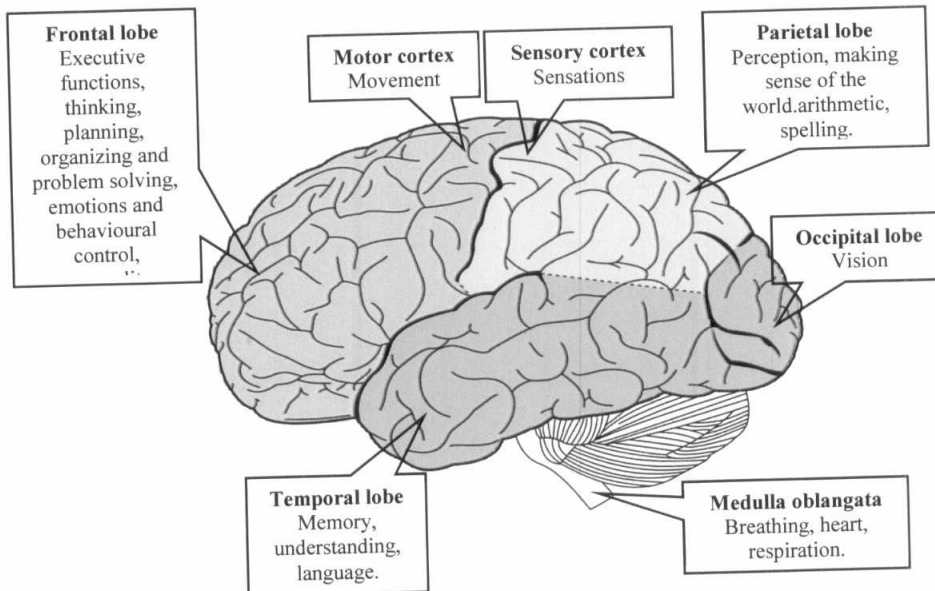
Figure 9 brain lobes and function for each lobe [14]

Notes by form Figure 9, the central-parietal lobe (P) its responsible on the spelling task, typically done recorded P300 signal from centro-parietal electrodes, therefore the electrodes its placed on the lobe (P) its responsible on the speller task, and correlated to this task, based on 10-20 system international.

Using independent component analysis (ICA) is a statistical procedure that splits a set of mixed signals into its sources with no previous information on the nature of the signal, using for actifact removal, the figures (10 –25), explain stimulus average feedback type, for all sessions, and all subjects, if value (0) then bad feedback (negative), if value (1) then good feedback (positive), respectively.
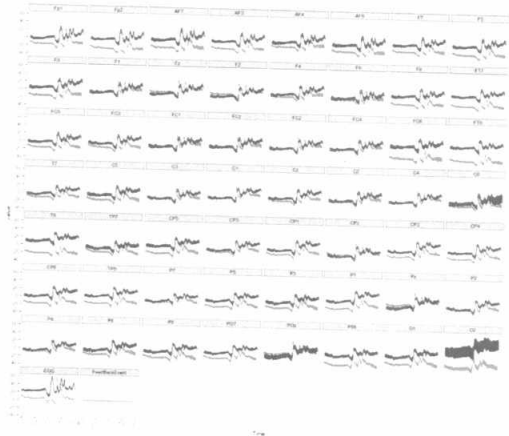
Figure 10: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 1 for all sessions.

Figure 11: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 2 for all sessions.
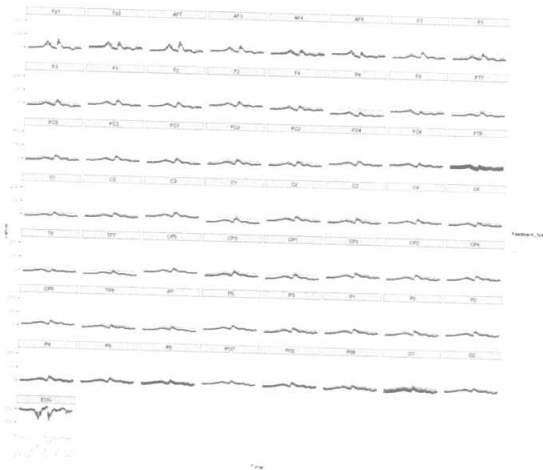
Figure 12: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 3 for all sessions.
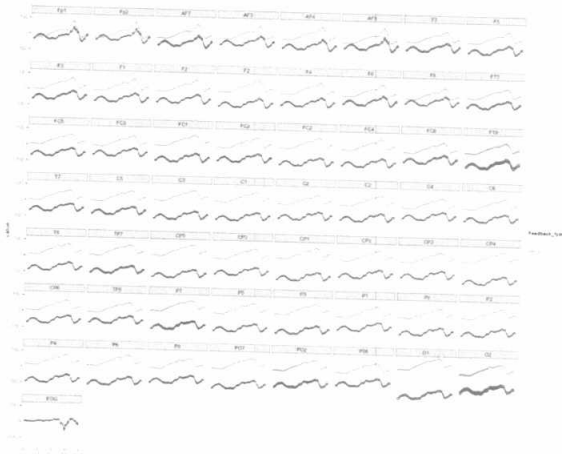
Figure 13: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 4 for all sessions.
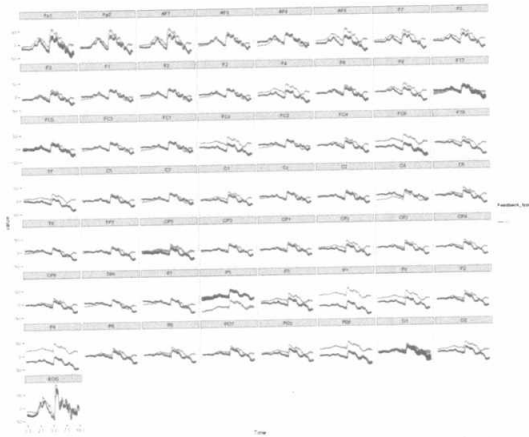
Figure 14: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 5 for all sessions.
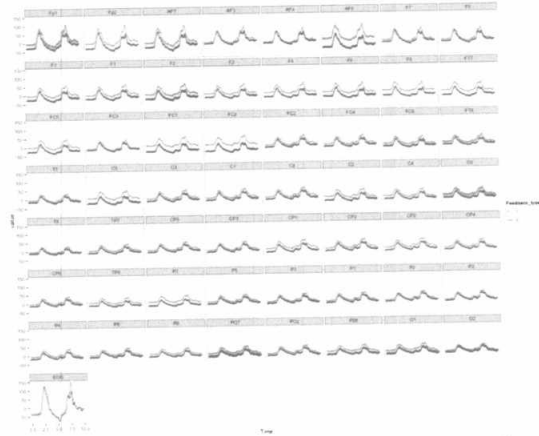
Figure 15: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 6 for all sessions.
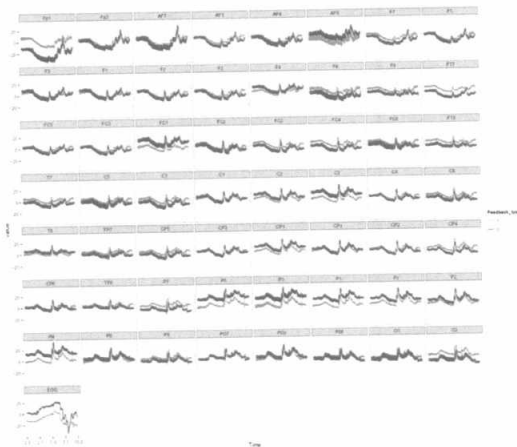
Figure 16: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 7 for all sessions.
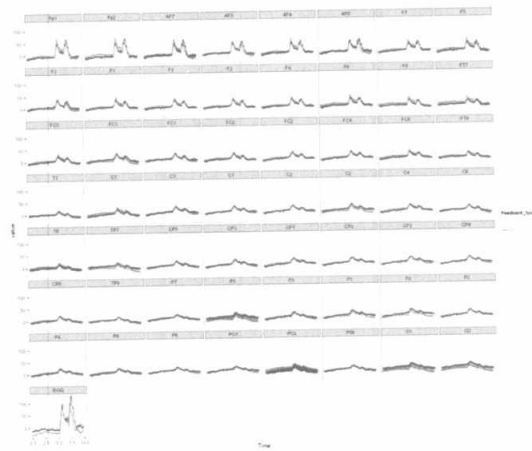
Figure 17: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 8 for all sessions.

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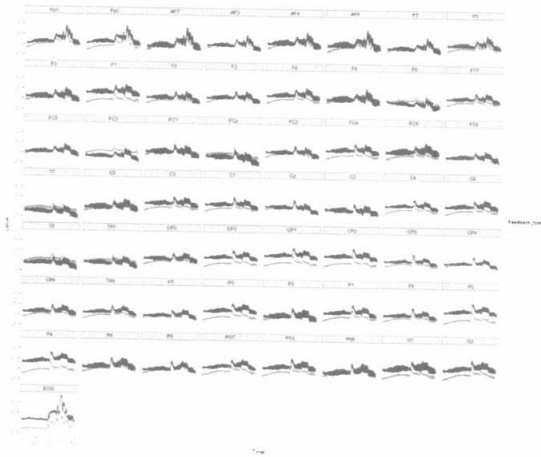
Figure 18: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 9 for all sessions.
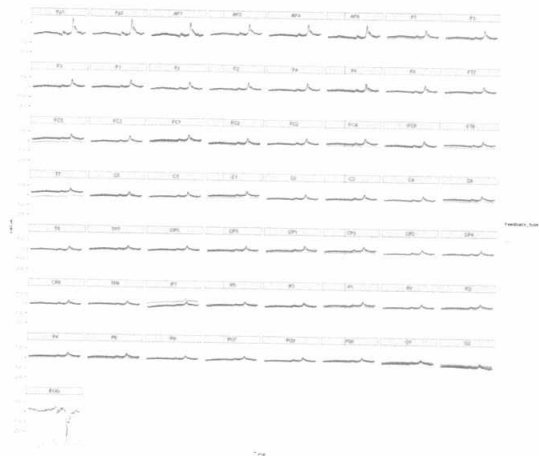
Figure 19: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 10 for all sessions.
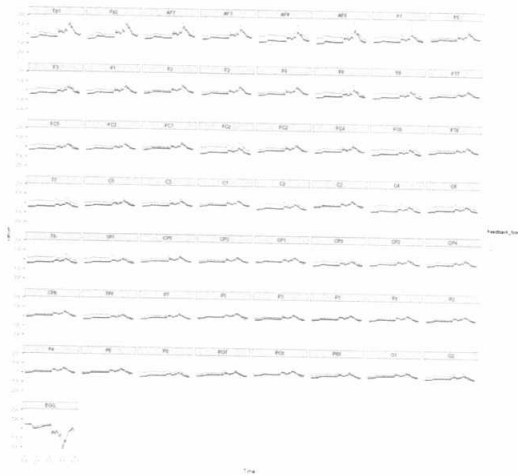
Figure 20: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 11 for all sessions.
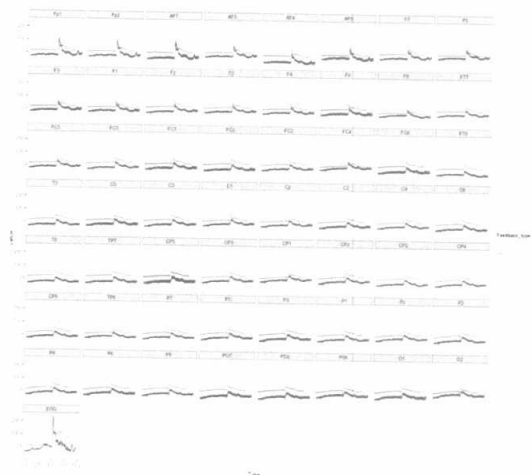
Figure 21: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 12 for all sessions.

Figure 22: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 13 for all sessions.
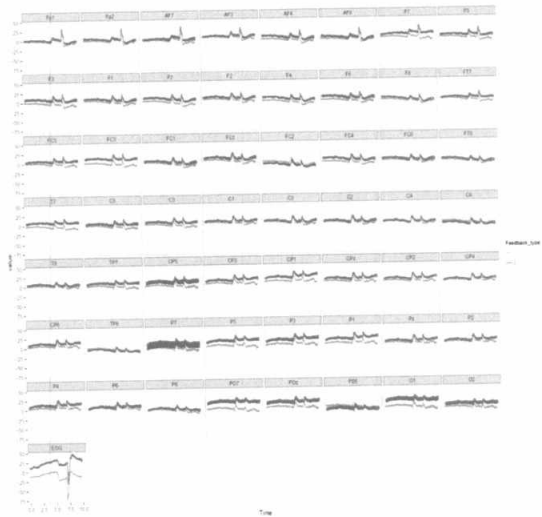
Figure 23: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 14 for all sessions.
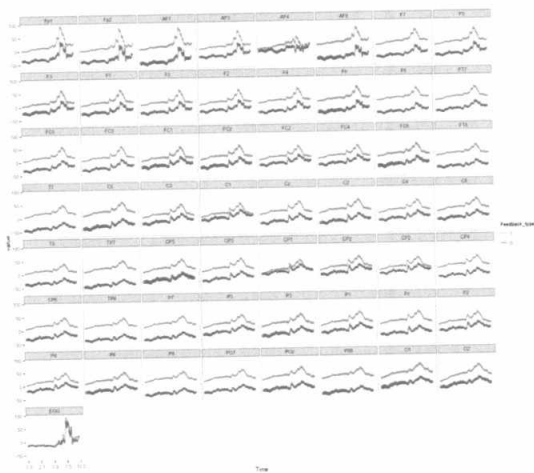
Figure 24: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 15 for all sessions.
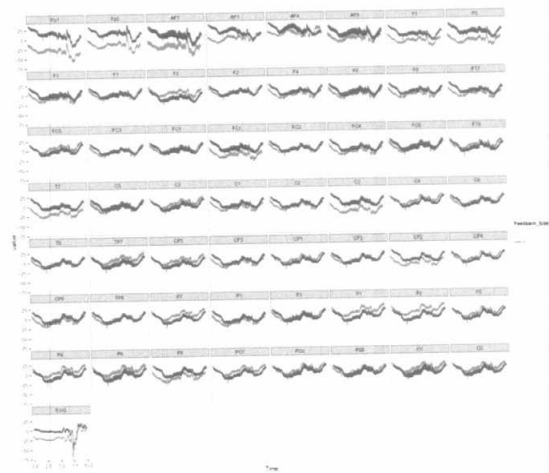
Figure 25: Show feedback type, if value (0) then bad feedback, if value (1) good feedback, stimulus average for subject 16 for all sessions.

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5.1. Summary of results:

5.1.1. Computing numbers of feedback (0 or 1) for all subjects and all sessions, explaining in table 4.

Table **4**: Explain numbers of feedback (bad (0) or good (1)), for each sessions for all subjects.

| Subjects	Session 1		Session 2		Session 3		Session 4		Session 5	
	Bad (0)	Good (1)	Bad (0)	Good (1)	Bad (0)	Good (1)	Bad (0)	Good (1)	Bad (0)	Good (1)
1	10	50	18	42	24	36	25	35	44	56
2	1	59	3	57	5	55	4	56	11	89
3	4	56	7	53	3	57	7	53	12	88
4	14	46	18	42	18	42	21	39	44	56
5	19	41	19	41	27	33	27	33	59	41
6	22	38	30	30	36	24	25	35	50	50
7	23	37	16	44	18	42	18	42	50	50
8	16	44	18	42	22	38	25	35	47	53
9	6	54	17	43	24	36	26	34	41	59
10	9	51	14	46	14	46	15	45	27	73
11	17	43	14	46	18	42	19	41	36	64
12	2	58	2	58	3	57	5	55	15	85
13	3	57	4	56	6	54	5	55	9	91
14	18	42	24	36	21	39	17	43	39	61
15	6	54	9	51	14	46	23	37	49	51
16	25	35	23	37	30	30	21	39	60	40

For each session (60) feedback (0 or 1), except last session (fifth 100 feedback (0 or 1)) for all subjects, and all sessions.

5.1.2. Computing average between feedback (0 and 1) for all subjects and all sessions, through the following equation:

$$Ave. = \frac{Sum\ of\ feedback\ (0\ \&\ 1)}{Total\ of\ numbers\ for\ feedback\ (0\ \&\ 1)} \qquad (2)$$

This is an equation for each subject in fifth of sessions, table 5 explaining the average for feedback.

Table **5**: Explain average of feedback (0 and 1), for all sessions, and all subjects.

Subjects	Average of feedback types for all sessions and all subjects				
	Session 1	Session 2	Session 3	Session 4	Session 5
1	0.83	0.7	0.6	0.58	0.56
2	0.98	0.95	0.91	0.93	0.89
3	0.93	0.88	0.95	0.88	0.88
4	0.76	0.7	0.7	0.65	0.56
5	0.68	0.68	0.55	0.55	0.41
6	0.63	0.5	0.4	0.58	0.5
7	0.61	0.73	0.7	0.7	0.5
8	0.73	0.7	0.63	0.75	0.53
9	0.9	0.71	0.6	0.56	0.59
10	0.85	0.76	0.76	0.75	0.73
11	0.71	0.76	0.7	0.68	0.64
12	0.96	0.96	0.95	0.91	0.85
13	0.95	0.93	0.9	0.91	0.91
14	0.7	0.6	0.65	0.71	0.61
15	0.9	0.85	0.76	0.61	0.51
16	0.58	0.61	0.5	0.65	0.4

5.1.3. As previously passed, from where number of feedback for each subject, in all sessions, the table 6 listing sequences of feedback for all subjects and all sessions.

Table 6: Explain the sequence of feedback for each subject in all sessions.

Subject 1	Session 1	11001011011101111111111010101111111011011111111111111111111
	Session 2	11000101100100111110010111110111101011011111111101110011
	Session 3	11111111010011111101100101101110100001011001101100101011000
	Session 4	11100111010111010110011100101001010111001010100110111001011
	Session 5	0010110010001111100101010000011100111100110111010111000010111011100110010010011110110110101110101011
Subject 2	Session 1	11110111111111111111111111111111111111111111111111111111111
	Session 2	11111111111110111111111101111111111111111111111111110111111111
	Session 3	11101111111110011111111111111111111111111111111111101111110
	Session 4	11111111101111111111111111111111111111111111101111001111111111
	Session 5	11111111111111101111111111111111011111111110100101111111111111111011111111101110111111111110111101111111
Subject 3	Session 1	1111110011111111111111111111111111111011111111111101111111111
	Session 2	11111101010011111111111111110111111111111111111111111111111100
	Session 3	101111111111111111011111111111111111111111111101011111111111
	Session 4	11101111111111111111111011110101111111111111111111101111111100
	Session 5	11111111111111111011111010110011111111111111111111111011111111110011111111110111101111011101111111
Subject 4	Session 1	1111110110101011111011011111000111011111011101111101101101111
	Session 2	00101111111111111011111111101111001011011010011000001111011
	Session 3	111111000011111010100011111111101111011101111111110011100010
	Session 4	010110010110111110010111111010101111110100110011000101011111
	Session 5	0111001001010001111100011000111010110001100100101010101111000110111111101001111110000010011111010
Subject 5	Session 1	0001111110111111111111111100111111010101011100000111010011 0
	Session 2	11010101011011100101111110010101101010011111111111110001 1
	Session 3	100101101011111001000001100100110111101110110111010000000 111
	Session 4	111100111011111100101011100101110001001010100010100110010 10
	Session 5	0110100100000001000010111110001000010111101000000011110111100010101110000100010011001010111010001000
Subject 6	Session 1	1101000110111101010011010011011111111111101000111101011001110
	Session 2	0101111110111101010010100100000100110110101010111101000100010 0
	Session 3	1010110110111100110100100000100100000000010100110110010100010
	Session 4	10101011011010100000110011111111100000101111110010110111100
	Session 5	11100110110001011100100111110110000110101100000110101001010001001000110111110000010011110000111110 0
Subject 7	Session 1	11010111101101111001111101001010000000101111110011111100011
	Session 2	11010111111111110100100110111111011111010100111001111111101
	Session 3	010110010101111111111111111101110110010011011000100111111111
	Session 4	11101001011111111011100111001011101111011010101011011111111011
	Session 5	0010100011000010100001100111101000101110011001011111100010101110111000011001101111010100000000101
Subject 8	Session 1	11110111101111011111001101001101100001111111111101111111001
	Session 2	1010011011011101111111111111011111100010010011110110010110 1
	Session 3	001011011001100101110011111101111110100010100111010101110011
	Session 4	011001111111010010000101000011010101011010111011111110010 1
	Session 5	11001101011011011111010010000111100111000000101001100010111011010001111111101111010100101000001000 1

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Subject 9	Session 1	0111111111111111111111111101111111111111111111101100111110111
	Session 2	1111111101110110111101111100001011001011111111110001101110
	Session 3	1110110111011101001101001000101011011011101111110010101010
	Session 4	111111101110011010000111000100000101100100011111101010101
	Session 5	111111111100000101011110110000110100111111111110010110110100101100011011010 11101011101001100011000
Subject 10	Session 1	111111110111111011100011101111011011101111111111111111
	Session 2	1111110111111010111001110111101111101011100111110011110
	Session 3	1111111111101011110101111111111111011010101101100101110011
	Session 4	110111100111111001110101111001111011111101111100100111110
	Session 5	10100111110011111111110011101101101111111100101111101000110011111010111101 101110101101111101101011
Subject 11	Session 1	1111111111001101111101111011100001111111101001000001011111
	Session 2	0110111111101111111101111111011100101111011000011111111101
	Session 3	11011000101111111011111111111101101100111000110010011101
	Session 4	1101101001011011010101111111011111000001110110010111111101
	Session 5	111010000101000110010110110111111011001101110011010001100101111101011011 111001101010110111111111
Subject 12	Session 1	11111111111101111111111111111111101111111111111111111111111
	Session 2	111101111111111111111111111111111111111111111111011111111
	Session 3	1111111111111001111111111110111111111111111111111011111111
	Session 4	11111111111111111111110101111111111111111110111011111110111
	Session 5	1101101111111111111010101111111110011111111111111011101111011111110110110 0111111111111011111011011
Subject 13	Session 1	11111111111111111111011111111111111111111111111111111001
	Session 2	1011111111111111111111111111111111111111111111101111100
	Session 3	11111110111111111111111111111111011111101101011101011111
	Session 4	11101111111111111110111111111111110111111111111110111110
	Session 5	111111101111111110101110111111111111111111111111111111111001111111111111 011111111111100110111111
Subject 14	Session 1	111111110001100101010011111010001111010011010111111111
	Session 2	00001100001111000011101001100011111111111110011000111111
	Session 3	11111011100111111101000111111011110110000110010101010101
	Session 4	101111110010000111110111110101110011011111101011110111011
	Session 5	1111000101100001111001011111101001100001001110101011101010001101111111111 10000111100111101010110
Subject 15	Session 1	11111111111111001111111111010011111111110111111111111111
	Session 2	111111101111111111111111011011101101011111101110011111
	Session 3	011111111110111111111110101011011111000011111110001111
	Session 4	11110101010101110100110010110010110110110101100101011111
	Session 5	101010110100110101100011001010001101000000001000000011111101111000101101 10111100011001100101111
Subject 16	Session 1	110011000111011101110101010010000111100101110011000110111
	Session 2	10100111111100000011111011001011110110111011111100011000
	Session 3	00001100101111011100100000111110001111111010100100000011010
	Session 4	11011100110011010111100000101110111111100110110100101111
	Session 5	1001100100010001100100101000110000101110010101001011100000001110100101000 01011000010001101101000

Each subject (340) feedback (0 or 1), (240) feedback for (1 – 4 of sessions), (100) feedback for session 5.

Future work:

The following suggestion uses in the future studies for evaluation or development the P300 speller robust and accurate, its: the researches evaluation the speller matrix making the letters are large size and coloring, and background coloring or none, using slow and fast mode. Using P300 speller for Arabic letters. Detection and correction errors event during P300 speller task whether offline and online.

Conclusion

In this paper a new method for increase accuracy of classification for P300 speller, including: Feature extraction using (PCA) based on percentage for good feedback (1) and bad feedback (0), good feedback (in.side) and bad feedback (out.side), Classification using (SVML) for computing numbers of feedback whether (0 or 1) for all subjects and all sessions, sequences of feedback (0 or 1) for all subjects and all sessions, computing average between feedback (0 or 1) for all subjects and all sessions. Finally calculated performance of each electrode using (ICA) whether correlated or uncorrelated speller task for all subjects and all sessions.

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