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THE EFFECT OF USING HAMMING WINDOW AND LINEAR PREDICTIVE CODING MODEL IN EEG-P300 SIGNALS CLASSIFICATION

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Abstract: In this paper, Fisher linear discriminant analysis (FLDA) is used to classify the EEGP-300 signals which are extracted from brain activities. In this case, at first the preprocessing algorithms such as filtering and referencing are applied to the raw EEG signal. Then, in order to create a model out of the signal, a linear predictive coding model with 6 order is used. So that the signal is reconstructed by extracting linear predictive coding (LPC) model parameters of each single trial, and then every signal trial is passed through the Hamming window by length 9. At last Fisher Linear Discriminant Analysis is used for classifying. In this paper, classification accuracy, the maximum bit rate and the convergence time to achieve stability in maximum accuracy of classification are computed to compare performance of the proposed method, Fisher Linear Discriminant Analysis with Linear Predictive Coding Model and Hamming Window (LPC+HAMMING+FLDA), to FLDA and LPC+FLDA. The implementation results show that the efficiency of the proposed method in terms of classification accuracy and convergence time to achieve stability in maximum accuracy is better than the other two mentioned algorithms. As example, at the proposed algorithm with 8 electrode configuration the S2 converges to the maximum accuracy after eleventh Block while this happens for two other algorithms after fourteenth Block and the total classification accuracy for this person at proposed algorithm is improved as 2.2% and 4% than respectively LPC+FLDA and FLDA algorithms.

Keywords: EEG signal, LPC, BCI system, Fisher linear discriminant analysis (FLDA), P300, Hamming window.

1. INTRODUCTION

The EEG signal is related to the signals which are measured during synaptic excitation of many pyramidal neurons of brain's crust, which can be measured using electromyogram machine. For recording these signals an Electrodecapis often used. The International Federation of Electro-encephalography and Clinical neurophysiology have considered special configurations for electrodes, that is called 10-20 and include 21 electrodes(Fig. 1)[1].

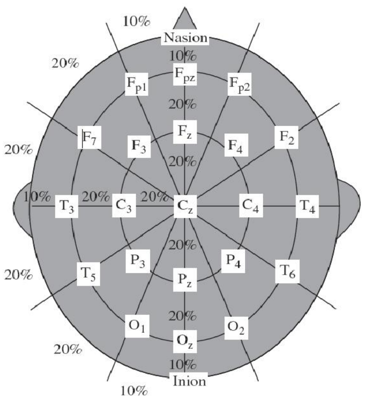

Fig. 1 – Arrangementof electrodesin global system of 10-20 [1].

Brain-Computer Interface is a way that brain can communicate with the outside universe [2]. In a BCI system, human brain activities are converted to computer usable commands and the purpose is to improve and develop the systems which are able to communicate with the outside universe and also control different organs of disabled people [3]. BCI is a communication and controlling system which is not dependent on the brain's output channels, which control muscular system (the user's intend is transmitted by brain signals not by the muscles) [4]. In a BCI system, by using brain signals that can be recorded in different ways, we could analyze mental intentions of a person. Basic researches on BCI systems began in the early 1970s, also in recent years attention has been considered. The advances in technology have led to variety of designing BCI systems. Nevertheless, quite a few of the described scientific systems are useful for disabled people; as a matter of fact BCI technology has not still progressed sufficiently to be used outside of the laboratory environments [5]. Today, there are different techniques for recording brain signals, which Electroencephalogram (EEG) signals are especially important due to noninvasive property and easy implementation. These signals reflect electrical activities in large group of nervous signals in brain. These electrical activities are recorded in skull via many electrodes in special arrangements. The Basic structure of a BCI system includes five stages as follows [6]:

- System Input includes raw EEG information which is received from electrodes connected to brain,
- Preprocessing stage consists of filtering the input EEG signal in order to noise reduction and increasing the signal to noise ratio,
- Translation process includes two parts; extraction and classification the features. Feature extraction includes extraction of valuable signals from input and classifying them into useable outputs for the next stage.
- Feature classification includes identifying feature patterns for simplifying the user's commands clustering.
- The classifier output is used for controlling the device. Device control process converts the classifier output into an action of device.

In designing a BCI system, many types of mental activities may be used. Generally these methods can be divided into two main groups based on their production [7]:

A) Using of stimulation input such as Visual Evoked Potentials (VEPs)

B) Using of Membrane potential, this requires no external stimulation.

P300 signal is an Event-Related Potential [4]. This signal can be recorded without using trained people and can be achieved by recording brain signals. P300 signal corresponds to a positive reflection on the voltage that appears in the brain signal 300 ms after stimulation [3]. In other words, when the brain is stimulated by light, 300 milliseconds after the stimulation, the reflection will appear [8]. The main application is for disabled people who suffer from severe muscle inability [9]. Thus they can communicate with the external world and also control the different organs of their body. This application is also used as a tool for rehabilitation [10]. The P300 potential first was used in the spelling systems, which helps disabled people to spell words. This operated by selecting the words containing the letters or symbols on a computer screen [11].

Useful information in BCI systems is at frequencies lower than 30Hz. Choosing a convenient method for signal amplification is dependent on several factors such as recording technology, the number of electrodes. Various processing techniques are used in this field such as the Spatial Filtering-Reference method [12], Principal component analysis [13], Independent Component Analysis [14], Common spatial patterns [15] and common spatial subspace decomposition [16]. In designing of a BCI system, some of the properties of these signals like as being noisy, high-dimensional and nonlinear and non-stationary must be considered. Various methods, based on BCI systems, are being used for extracting useful features out of these signals, some of these methods include band power, correlation between EEG band power and signal representation in the frequency domain [17].

Many classifiers have been used in designing of BCI systems. The most commonly used classifiers in this case include the linear discriminant classifiers [17], neural networks, K-means classifier and combination of classifiers [18], nonlinear Bayesian classifiers [19].

2. DATABASE

The database using in this paper includes recorded EEG signals, 5 healthy people and 4 disabled, is introduced in [5]. Subjects S1 and S2 were able to move their hands slowly and it was possible to communicate with them verbally. These people were suffering from speech disorders. Subject S3 was able to move his left hand but it was not possible to communicate with him verbally and was only able to communicate by telling yes or no. Subject S4 had low ability to control his hand movements but he had ability of verbal communication. Subject S5 had no ability to control movements of his hand and it was too difficult to communicate with. So his data was removed out from being taken into account because of the low validity of his data. Subject S6 to S9 had no problem in their physical condition. Everyone was tested in four stages, in each stage 6 tests was done by each subject, two of them were performed at one day and the next two stages at another day within two weeks. In this test, for all the stages, 6 images would be randomly shown to every person with time interval of 400 *ms* and they would be requested to count the number of times that a particular image was seen (in each test one different image was counted, so 6 tests for 6 images). This was done for between 20 and 25 times, but the order of appearance of images would change randomly for each time. All the 6 images in this test make a block and total number of blocks in all 6 tests is between 20 and 25. EEG signal was recorded by the electrodes connected to these people while they were seeing the images. Four configurations of electrodes had been used in this test, which include 4-electrode, 8-electrode, 16-electrode and 32-electrode configurations [5].

In this paper, the validation of obtained results is based on *k-fold* method in which k refers to the number of repetitions and it is 4 in this paper. So, based on this method, 75% of samples are used for training and the remaining 25% of samples are used for test and this is done for 4 times by using different samples as training and test and the conclusion would be taken into account by averaging the 4 different test sample results.

3. THE PROPOSED ALGORITHM

The proposed algorithm for designing BCI system is shown in Fig. 2. The main steps that would be discussed in the following are as follows:

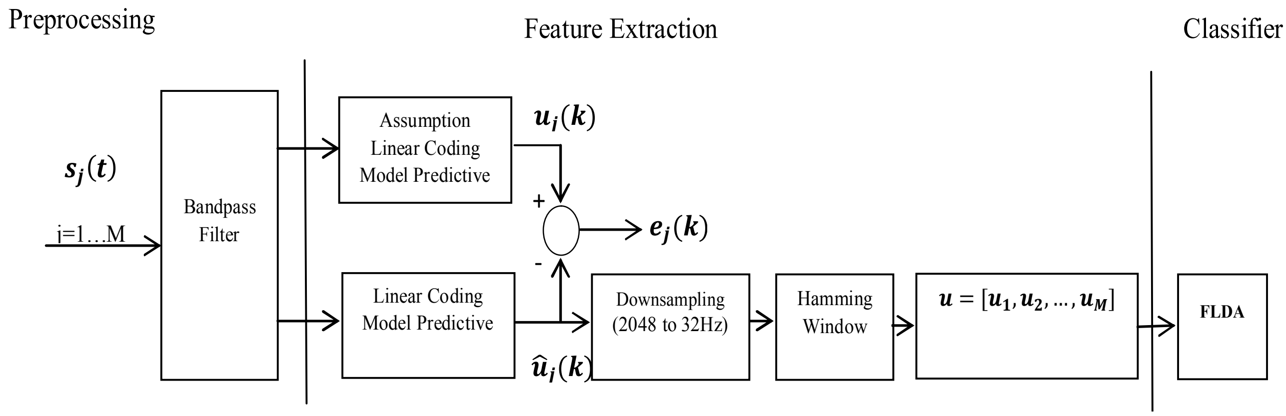

Fig. 2 – Block diagram of the proposed algorithm.

3.1 EEG SIGNAL PREPROCESSING

In this stage the raw EEG signal is prepared for feature extraction. At first, the raw signal is referenced, for increasing signal to noise ratio, for this, the two earlobe electrodes are used as reference electrodes, then, in order to eliminate the noise, a 6th order Butterworth bandpass filter is used with cut-off frequency of 1Hz and 12Hz. After this stage signal trials will be extracted. The length of each signal trial is one second. Every single trial begins with the appearance of an image. The appearing interval of each image with the next image is 0.4 second. Thus every single trial consists of desired image with a length of 0.4 and the sequences of other images with a length of 0.6 seconds; this is done to ensure that every single trial contains the desired image signals [5].

3.2 EXTRACTING MAIN FEATURES BY APPLYING LINEAR PREDICTIVE CODING MODEL

The main purpose of extracting features is to find brain signals related to mental activities. For this purpose, Linear Predictive (LPC) Model is used for modeling the signal after preprocessing stage. Its main idea is that one signal can be estimated based on a linear combination of the previous samples. The prediction coefficients can be calculated by minimizing sum of the errors between the real signal and the estimated samples. Assume that $s_j(t), j = 1...M$ (M is the number of electrodes) is the input of the bandpass filter at moment of t and $\hat{u}_j(k), j = 1...M$ is the estimated value of signal obtained by applying LPC model, in which K is the number of trial signals samples (K=2048). $\hat{u}_j(k)$ Can be computed as a linear combination of previous calculated p sample [20]:

$$\hat{u}_j(k) = \sum_{i=1}^{p} a_j(i) u_j(k-i), \tag{1}$$

In which $\{a_j(i)\}$ is called the linear estimated coefficients. In this article p is considered 6, as the best result. Prediction error e (k) between the observed value $u_j(k)$ and the estimated amount $\hat{u}_j(k)$ is defined as follows:

$$e(k) = u_j(k) - \hat{u}_j(k) = u_j(k) - \sum_{i=1}^{p} a_j(i) u_j(k-i), \tag{2}$$

Estimated coefficients of $\{a_j(i)\}$ can be determined optimally by minimizing the sum of squared errors:

$$E_j = \frac{1}{N} \sum_{k=0}^{N-1} e^2{}_j(k) = \frac{1}{N} \sum_{k=01}^{N-1} \left(u_j(k) - \sum_{i=1}^{p} a_j(i) u_j(k-i) \right)^2, \tag{3}$$

In order to solve equation (10), we should differentiate E with respect to a_k and setting it equal to zero; the following equation would be obtained:

$$Ra = r, \tag{4}$$

where (R) is the autocorrelation matrix with p × p dimension, (r) is an autocorrelation vector with p× 1 dimension and (a) is a vector with p × 1 dimension that contains the prediction coefficients [20].

3.3 DOWNSAMPLING

In this stage, after modeling the signal, we reduce the sampling frequency of the signal (2048Hz to 32Hz) [5]. The next step is windsorizing which removes the top and bottom 10% of the sample's amplitudes. Next step includes scaling signals (1,-1) [5].

3.4 HAMMING WINDOW

In this algorithm, as shown in Fig. (2), a Hamming window with length 9 is used as a filter on each set of sequences (trial) that each set includes 32 samples. Every single trial consists of a sequence with length 1 second which includes examples of the desired image by length of 0.4 seconds and 0.6 seconds with the other images. A good way to separate or highlight the desired image sequences is using a non-square window (Fig. 3); that among these windows, hamming window offers the best answer to this algorithm.

Finally, the feature vector is formed using different configurations of electrodes [5].

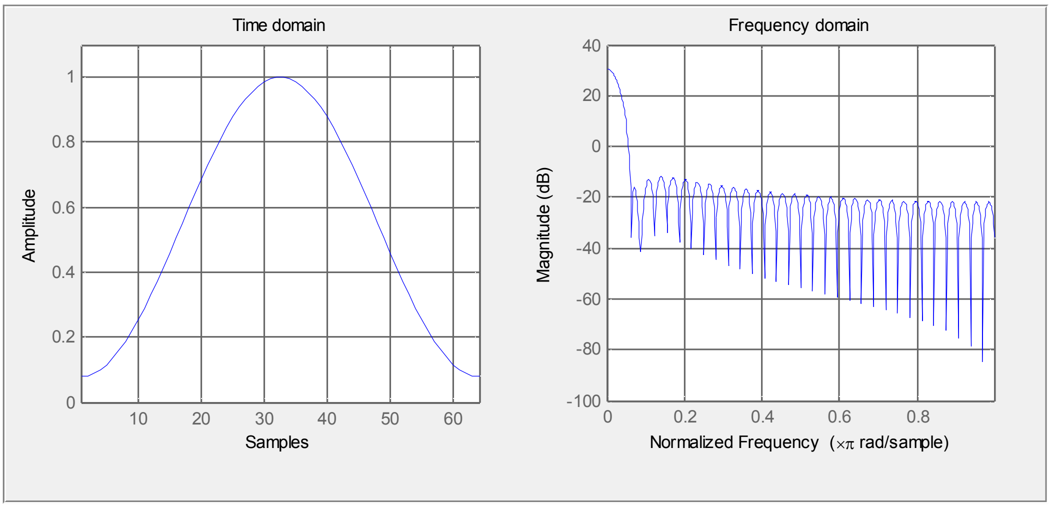

Fig. 3 – Hamming window with N=64.

3.5 FISHER LINEAR DISCRIMINANT ANALYSIS

Linear discriminant analysis or Fisher linear discriminant analysis is used successfully in many BCI system's applications such as P-300, multiple-class BCI, etc. Requiring low computational complexity and good results are the main advantages of this classifier.

The purpose of this classifier is to compute a discriminator vector which can separate two or more classes. Here we consider only two classes. Consider we are given a set of input vectors Xi(i=1…….N) and corresponding class-labels are Yi= {-1, 1}. In which N1 is the number of training examples for class Yi = 1(class C1) and N2 is the number of training examples for class Yi = -1(class C2), and N=N1+N2 then the objective function for computing a Weight vector (W) is [5]:

$$J(W) = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}, \tag{5}$$

Where

$$\mu_k = \frac{1}{N_k} \sum_{i \in C_k} w^T x_i \ , \ \sigma_k^2 = \sum_{i \in C_k} \left(w^T x_i - \mu_k \right)^2, \tag{6}$$

In order to compute the optimal discriminant vector for training data set directly, matrix form for the quantities $(\mu_1 - \mu_2)^2$ and $\sigma_1^2 + \sigma_2^2$ can be used. By defining the class means m_k. $m_k = \frac{1}{N_k} \sum_i x_i$ And defining the between-class scatter matrix (S_B) and the within-class scatter matrix (S_W) as follows:

$$S_B = (m_1 - m_2)(m_1 - m_2)^T, \tag{7}$$

Which m_1 and m_2 are first and second class means, respectively.

$$, \quad (8)$$

$$S_W = \sum_{k=1}^{2} \sum_{i \in C_k} (x_i - m_k)(x_i - m_k)^T$$

Using equations (7) and (8) the related FLDA classifier projection function (9) can be wrote as:

$$J(w) = \frac{w^T S_B w}{w^T S_W w}, \quad (9)$$

By computing the derivative of J can be found that the optimal value of W satisfies the following equation [5]:

$$w \propto S_W^{-1}(m_1 - m_2), \quad (10)$$

The most important feature of FLDA classifier is its simplicity. This classifier is useful especially, when the number of features is small and the number of feature vectors is large.

The main problem in FLDA classifier is that the between- class scatter matrix can become singular, so the inverse of $S_W$would become ill-defined. In particular this happens when the number of features gets larger than the number of training examples. In [21] a method is proposed to solve this problem. By applying this method in FLDA algorithm the optimal w satisfies the following equation [21]:

$$w \propto \left(S_w + \lambda I\right)^{-1} (m_1 - m_2), \quad (11)$$

Where λ has small amount (in this paper .001 is considered) and I is identity matrix.

4. PARAMETERS TO EVALUATE THE PERFORMANCE OF THE PROPOSED ALGORITHM

Parameters to evaluate the performance of the proposed algorithm consist of three parts including general classification accuracy, the maximum bit rate and convergence time to achieve stability in maximum accuracy.

- General classification accuracy

General accuracy is calculated for each block separately. The accuracy of each block is dependent on the previous blocks, in this way that in the first block the output of the classifier for the desired image and the other 5 images (each block consists of 6 images) is computed and if the maximum is belonged to the desired image, in the block and the test, we consider true or 1 for this block otherwise 0, then for the second block this process is done but the output of the classifier for this block is summed up with the result of the previous block, after that if the maximum is belonged to the desired image the result of this block is 1 otherwise 0 and this process is done for the 20 blocks , this is done on the 6 tests for the 4 stages, separately, and the process average would be calculated, so the general accuracy for each block would be obtained and finally the average of the twenty blocks, it was used just 20 blocks, gives out the overall accuracy [5].

- the maximum bit rate

This criterion is the number of bits sent from each of the tested persons to a BCI system which is defined in time unit and obtained from following equation [21]:

$$b(N,p,t)=\left(log_2(N)+ plog_2(p)+(1-p)log_2\left(\frac{1-p}{N-1}\right)\right)\frac{60}{t}, \quad (12)$$

Where N is the number of different commands sent by the user to the system and P is the probability of correct diagnosis of the system and t is the time needed to send a command. According to equation (12), the higher classification accuracy cause the sent bit rate, increases and this will be more effective in the first block of the proposed algorithm. Maximum sent bit rate for each block is computed as the accuracy was calculated for each block. Finally, to obtain the general maximum sent bit rate, average of twenty blocks would be computed.

- convergence time to achieve stability in maximum accuracy

It is a criterion of convergence time to achieve maximum accuracy. This assesses the algorithm that how fast the classification accuracy has reached to 100 percent.

5. THE IMPLEMENTATION RESULTS

Classification accuracy of the proposed algorithms (LPC+Hamming+FLDA) and LPC+FLDA and FLDA algorithms in 8 and 16-electrode configurations are illustrated in Tables 1 and 2. According to Fig. 4, the proposed algorithm LPC+HAMMING+FLDA with 8 electrodes configuration for S2 and S7 in case of convergence time to achieve maximum accuracy and general classification accuracy is better than the other two algorithms. Also for people S4, S3 and S8 proposed algorithm has better performance with respect to the same criteria.

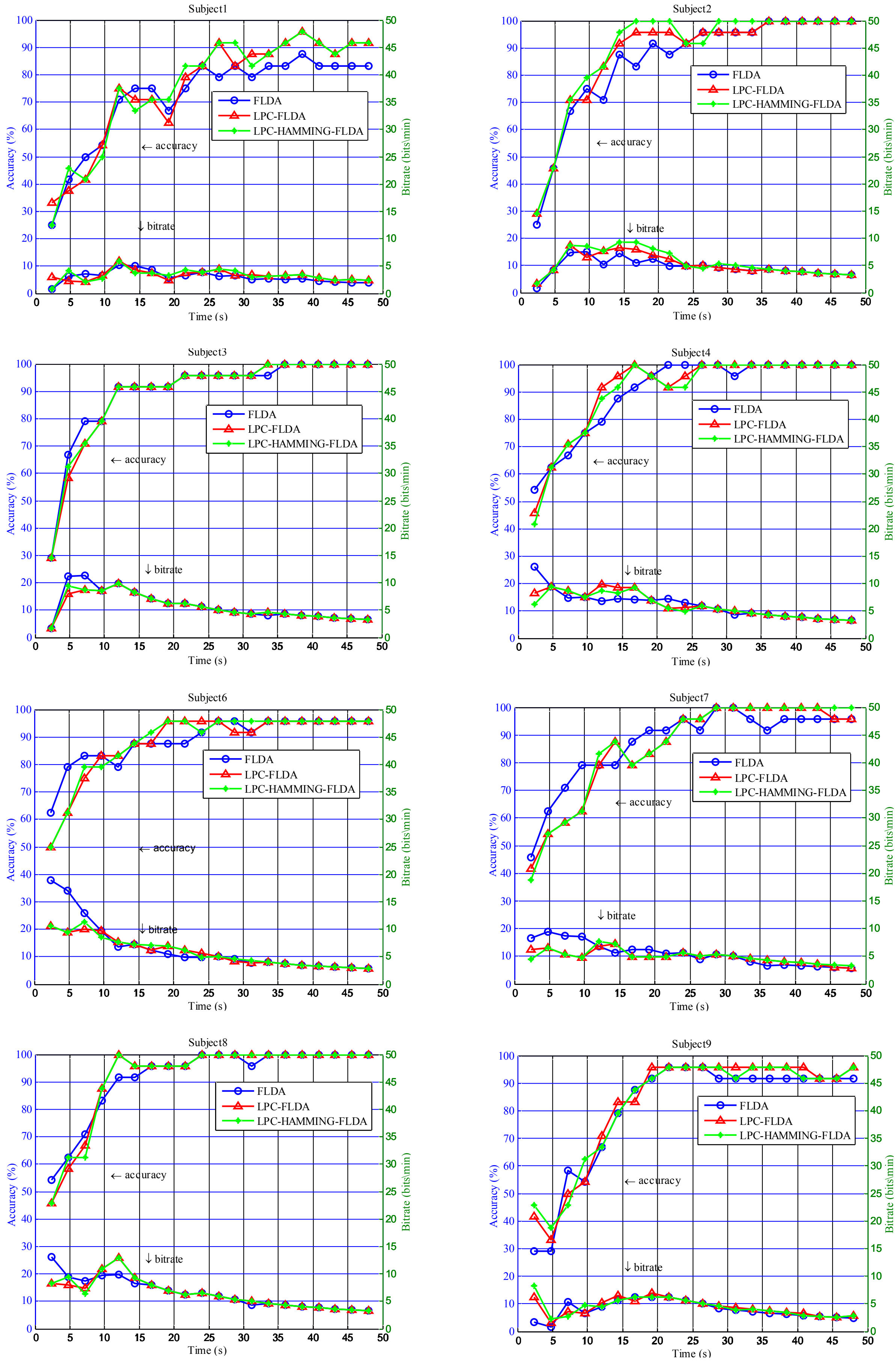

Fig. 4 – Comparison of the proposed algorithm LPC+ HAMMING+FLDA with FLDA and LPC+FLDA algorithms in case of 8-electrode configuration.

According to Fig. 5, the proposed algorithm with configuration of 16 electrodes for persons S1 and S4 has done better than the two LPC+FLDA and FLDA algorithms in order to convergence time to achieve maximum accuracy and general classification accuracy. Also for persons, S3, S7, S8, and S9 proposed algorithm's results are better than FLDA.

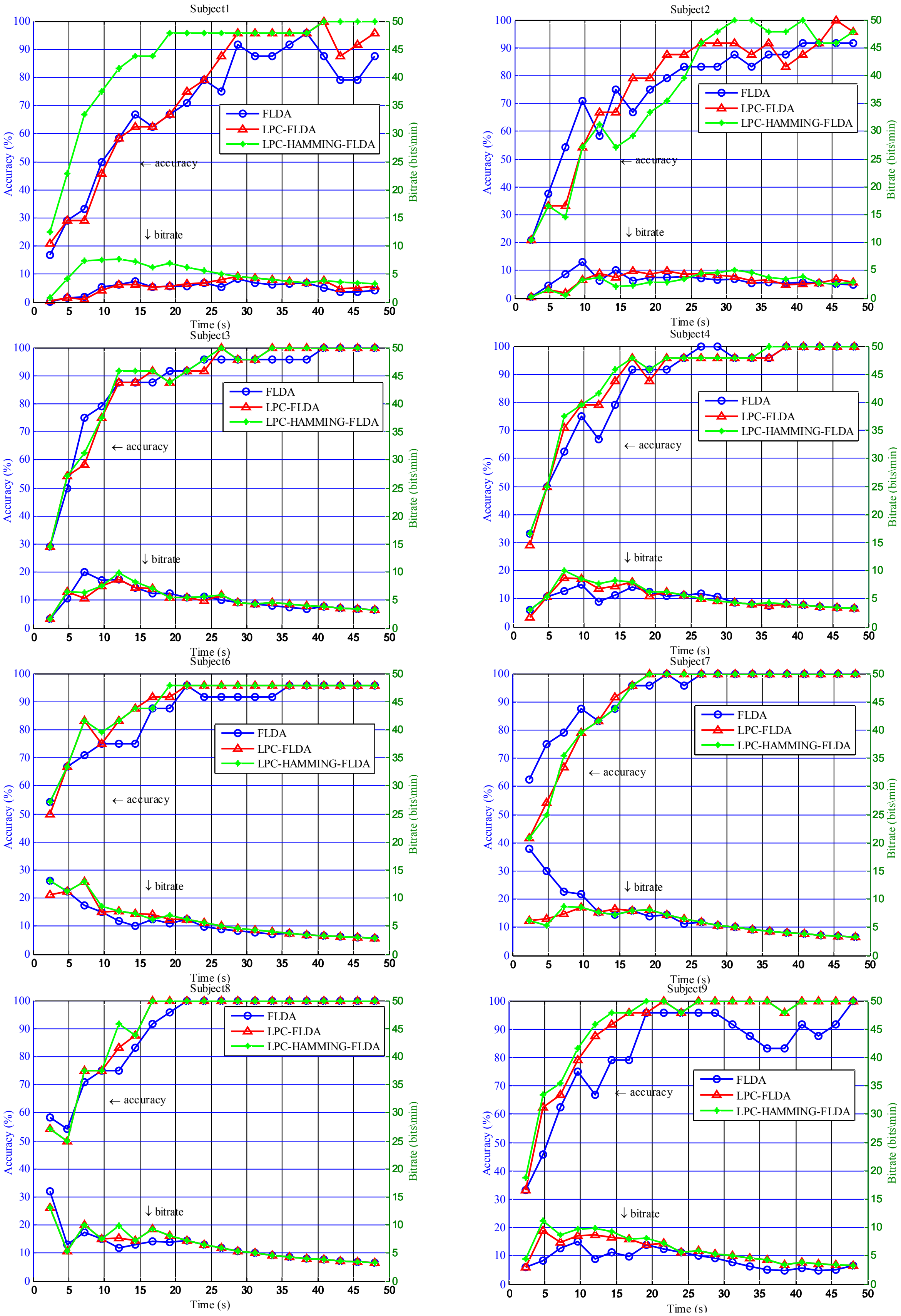

Fig. 5 – Comparison of the proposed algorithm LPC+HAMMING+FLDA with FLDA and LPC+FLDA algorithms in case of 16-electrode configuration.

Table1. Comparison of classification accuracy of the proposed algorithm with two LPC+FLDA and FLDA algorithms in case of 8-electrode configuration.

SUBJECT	FLDA	FLDA+LPC	FLDA+LPC + HAMMING
S1	72.3	75.4	75.8
S2	85.4	87.7	89.4
S3	89.8	89.2	89.4
S4	90.4	91.2	90.4
S6	89.2	88.3	88.7
S7	87.1	85.8	86.2
S8	91.9	92.1	92.1
S9	80.4	82.7	82.5
Average (S1-S4)	84.5±8.4	85.9±7.1	86.2±7.0
Average (S6-S9)	87.1±4.9	87.2±3.4	87.4±4.0
Average (all)	85.8±6.6	86.6±5.2	86.8±5.3

Table 2. Comparison of classification accuracy of the proposed algorithm with two LPC+FLDA and FLDA algorithms in case of 16-electrode configuration

SUBJECT	FLDA	FLDA+LPC	FLDA+LPC + HAMMING
S1	69.8	73.5	74.4
S2	75.0	76.0	77.9
S3	87.5	83.3	88.1
S4	86.2	87.5	88.7
S6	86.0	89.0	89.4
S7	93.1	90.6	90.4
S8	90.2	91.2	91.7
S9	81.9	90.2	91.7
Average (S1-S4)	79.6±8.6	81.1±7.6	82.3±7.2
Average (S6-S9)	87.8±5.0	90.2±1.6	90.8±1.1
Average (all)	83.7±6.8	85.6±4.6	86.5±6.6

6. CONCLUSION

The proposed algorithm LPC+FLDA with hamming window (LPC+Hamming+FLDA) has provided better performance than the two LPC+FLDA and FLDA algorithms in case of convergence time to achieve maximum accuracy and the total classification accuracy**.** According to Fig. 4, as an example at the proposed algorithm with 8 electrode configuration the S2 converges to the maximum accuracy after eleventh Block while this happens for two other algorithms after fourteenth Block. This superiority is also visible in other persons**.** Regarding to Fig. 5, as an example at the proposed algorithm with 16 electrode configuration the S1 converges to the maximum accuracy after sixteenth Block while the other two algorithms are not converged to the maximize accuracy.

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