The Nucleus **50**, No. 1 (2013) 45-51

The Nucleus
A Quarterly Scientific Journal of Pakistan Atomic Energy Commission
NCLEAM, ISSN 0029-5698

EFFICIENT CLASSIFICATION USING MULTIPLE MENTAL THOUGHTS

A. ZAFAR, M.I. AHMAD[1] and *A. HANIF[2]

Department of Electrical Engineering, Wah Engineering College, University of Wah, Wah Cantt, Pakistan

[1]Visiting Faculty Member, Department of Electrical Engineering, Wah Engineering College, University of Wah, Wah Cantt, Pakistan

[2]Department of Electrical Engineering, Wah Engineering College, University of Wah, Wah Cantt, Pakistan

(Received December 27, 2012 and accepted in revised form March 13, 2013)

Researches in personal identification show that classification using multiple mental thoughts increases complexity and system's processing time. In this paper, an efficient classification algorithm is proposed to classify an individual using multiple mental thoughts. Features from Electroencephalography (EEG), used as biometric, are extracted using sixth order Autoregressive (AR) model, and Linear Discriminant Analysis (LDA) based classification is performed based on best mental thought combinations. Matlab® simulation results indicate that the proposed algorithm reduces the complexity as well as the processing time that confirms the use of EEG as a biometric for personal identification.

Keywords : Autoregressive (AR), Mental Thoughts (MT), Electroencephalography (EEG), Linear Discriminant Analysis (LDA)

1. Introduction

Recently, researches are made for finding new techniques of personal identification to make the personal identification system secure. In literature, many biometric techniques for personal identification have been developed including fingerprints [1], voice [2], facial features [3], palmprint [4], iris [5], hand geometry [6], heart signal [7], ear force field [8], and Visually Evoked Potential (VEP) [9]. Among all aforementioned techniques, fingerprints as a biometric are frequently used because of its ease of use [1].

Previously used biometrics are found prone to deception because they can easily be forged or can be stolen. Currently, researchers of biometric focus on finding new ways of biological features, which should be distinctive, cannot be reproduced and hence increases the security. A comparatively new among all biometric techniques based on electroencephalography (EEG) is proposed [10]. The EEG as a biometric provides several benefits upon forging, confidentiality, and impossible to steal. Poulos [11] used EEG spectral analysis for the extraction of features, by fitting a linear model of the AR type on the alpha rhythm EEG signal. These features fed into the Feed Forward Neural Network to classify among different individuals. A study by R.B. Paranjape [10] employed multi ordered AR models to distinguish between 40 subjects using 8 channel EEG data of each subject. The coefficients of model (features) were then classified using LDA with classification rate of 82%. Nae-Jen Huan and R. Palaniappan [12] investigated the performance of different AR features for Brain Computer Interface (BCI) design using different mental task combinations on Keirn and Aunon's data [13]. They investigated all possible two mental thoughts combinations for all subject. The 6^{th} order AR model is used for extracting features with Burg's, Least Square (LS) and Least Mean Square (LMS) algorithm. The computation of classification error rate is based on the comparison between Neural Network (NN) and LDA as a classifier. The results suggested that the classification performance of LDA is better than the classification performance of NN. As per literature review, classification of individual using multiple mental thought is first time proposed by R. Palaniappan [14]. Burg's algorithm is employed to extract AR coefficients (features), and then feature of individuals were classified using LDA. The results show that the classification error reduces with the increase in mental thoughts. The minimum classification error of 0.1% is achieved when five mental thoughts of one subject are combined. R. Palaniappan [15] proposed a novel technique to classify subjects using EEG signals from imagined activities. The sixth order AR model with Burg's Algorithm is used to extract the features from different imagined activities. Feature vector consist of AR coefficients, channel spectral power, inter-

* Corresponding author : dr.aamirhanif@wecuw.edu.pk

hemisphere channel spectral power differences and inter-hemisphere channel coefficient values. Classification error upto 0% is achieved using LDA classifier.

It is suggested that the classification error reduces as the number of mental thoughts are increased [14-15]. In this paper new efficient classification algorithm is proposed based on the selection of best mental thought followed by the reduction of possible combinations of two, three and four mental thoughts. The proposed algorithm reduces the computational complexity and the time required for processing. This paper is organized as follow. In Section 2 the acquisition of EEG signal and feature extraction using AR model are described. Efficient Classification algorithm based on LDA is explained in Section 3, and results are discussed in Section 4. The finding of this study is summarized in Section 5.

2. Data Preprocessing

2.1. Data

In this research work, EEG data of four subjects from Keirn and Aunon data is used [13]. The EEG data was collected in noise controlled room. The positions of electrodes C3, C4, P3, P4, O1 and O2 using 10-20 system is shown in Figure 1.

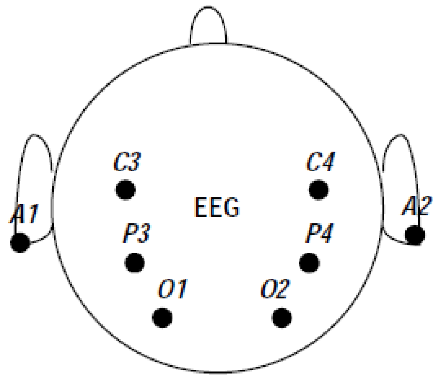

Figure 1. Electrode Placement [14].

The recording of EEG is based on referential montage technique in which electrically linked mastoids A1 and A2 are used as reference electrodes. The sampling rate at which EEG data were recorded is 250 Hz. Each subject was asked to perform five different mental activities including baseline, multiplication, geometric figure rotation, letter composing and visual counting tasks. The task relating baseline included the activity of relaxing and thinking of nothing in order to use measured EEG signal as a baseline. In Multiplication task, subjects were asked to perform the activity of solving a non-trivial multiplication problem such as 79 multiply by 64 without vocalization and without making any physical movement. Geometric figure rotation task is a practice of imagining a three dimensional object rotated about an axis. The task of subject in mental letter composing is to generate EEG imaginary data by writing a letter to a friend without vocalization. Visual counting task is an exercise of visualizing number written on whiteboard. For each task EEG data were recorded for 10 s and each task was repeated for 10 sessions. The segment consists of 2500 samples. Segment is further divided into 20 segments of 0.5 s.

2.2. AR Feature Extraction

EEG signal contain useful information which is extracted using a process known as features extraction. In this research work, AR model is used to extract features from different mental thoughts. The p^{th} order non deterministic AR model is given below [14].

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \tag{1}$$

Where, p is the order, $x(n)$ is a sampled signal at a point n, $e(n)$ represent the error terms which is independent of past samples and a_k are the coefficients of AR model. The coefficients are estimated using sixth order AR model based on Burg method [16]. Burg method is used to minimize forward as well as backward prediction errors in a signal by fitting AR model using more data points. The authors in [13-17] suggest that the features extracted using 6^{th} order AR model for multiple mental thoughts are good enough for further processing.

3. Efficient Classification

3.1. Linear Discriminant Analysis

The individual classification is performed by a classifier that divides data into different classes, and is trained in such a way that it identifies the relationship between the features and emotions that belongs to one of the particular class of the EEG signal. LDA is used as a classifier because it is computationally more attractive as compared to the other classifiers (e.g. Artificial Neural Network) [18]. The mathematical function used for classification of different group of data using LDA is as follows [14] :

$$F = \sum_{i=1}^{N} x_i w_i \quad (2)$$

x_i is a feature vector of AR coefficients, N is the length of feature vector which depends on total number of mental thoughts used, and w_i are the LDA weighted vector coefficients generated during the training of data. This function is designed such that it maximizes the inter-variance between the groups and minimizes the intra-variance within the groups. The consistency of the classifier results is enhanced by using 10 fold cross-validation. The performance criterion for the evaluation of classifier is based on the classification error given in eq. (3).

$$\%\ \text{Classification error} = \frac{\text{No of classified features in transformed data}}{\text{Total no. of features in transformed data}} \quad (3)$$

3.2. *Efficient Classification Algorithm – Best Mental Thought (BMT) Based Classification using LDA*

The proposed efficient classification algorithm can be divided into two parts

i. Selection of BMT

ii. Reduction of combinations based on BMT.

The computational steps for this algorithm are as follows:

3.2.1. *Best Mental Thought Selection*

1. The extracted features of each single mental thought i.e. Y_i of all subjects (X) should be input simultaneously to the classification system.
2. LDA is used to classify each single mental thought to determine the classification errors.
3. The process is repeated at least five times for a fair comparison with [14] to obtain minimum, maximum and average classification error ($e_{avg,\,k}$) using 10 fold cross-validations.
4. On the basis of minimum average classification error ($e_{avg,\,k}$), BMT is selected.
5. If the e_{avg} of BMT is equal to 0%, the person is declared to be fully classified [15].

3.2.2. *Reduction of Combinations Based on BMT*

1. If the average classification error is not equal to 0%, the features of best mental thought are combined with the features of remaining mental thoughts to form two mental thoughts combination. The two mental thought combinations are again processed through step 2 to step 5.
2. The process of concatenation of best selected mental thoughts and determination of average classification error is continued until all possible combinations of BMT are processed completely.

The scheme for efficient classification algorithm is illustrated with the help of a flow chart shown in Figure 2.

4. Results and Discussion

The 10-sec recorded EEG data is divided into 20 segments with each segment is length of 0.5 seconds and each task is repeated 10 times. So, a total of 800 features are extracted for four subjects. The sixth order AR model gives six coefficients for one electrode. As there are six electrodes therefore, the feature vector for single mental thought consists of 36 AR coefficients. Combination of two mental thought constitute a feature vector having length of 72 and similarly 108, 144, 180 for three four and five mental thoughts respectively. The 10 fold cross-validation divides these features into ten equal parts. For each time training and testing of classifier is based on the random selection of these folds. The process is repeated five times in order to evaluate minimum, maximum and average classification error. Table 1 gives the comparative analysis of classification error and processing time required to classify an individual using 10 fold cross-validation between the method used in [14] and in this research. Selection of single BMT is based on the minimum average classification error which is 2.675% for the multiplication task. The author in [14], reported the processing time for personal identification using multiple thoughts is 40 µs for one, 77.5 µs for two, 155 µs for three, 235 µs for four and 390 µs for five mental thoughts. For a fair comparison, it is assumed that system having same specifications as discussed in [14] is used. Therefore, the same processing time for personal identification using multiple mental thoughts as described in [14] is used. The processing time required to process all five single mental thought is 200 µs as shown in Table 1. The average classification error is not equal to 0%, so the features of multiplication task (single BMT) will combine with the features of remaining mental thoughts to form two mental thoughts combination. The possible combinations of two mental thoughts based on BMT are reduced to 4 from 10 as described in [14]. It is also observed that the

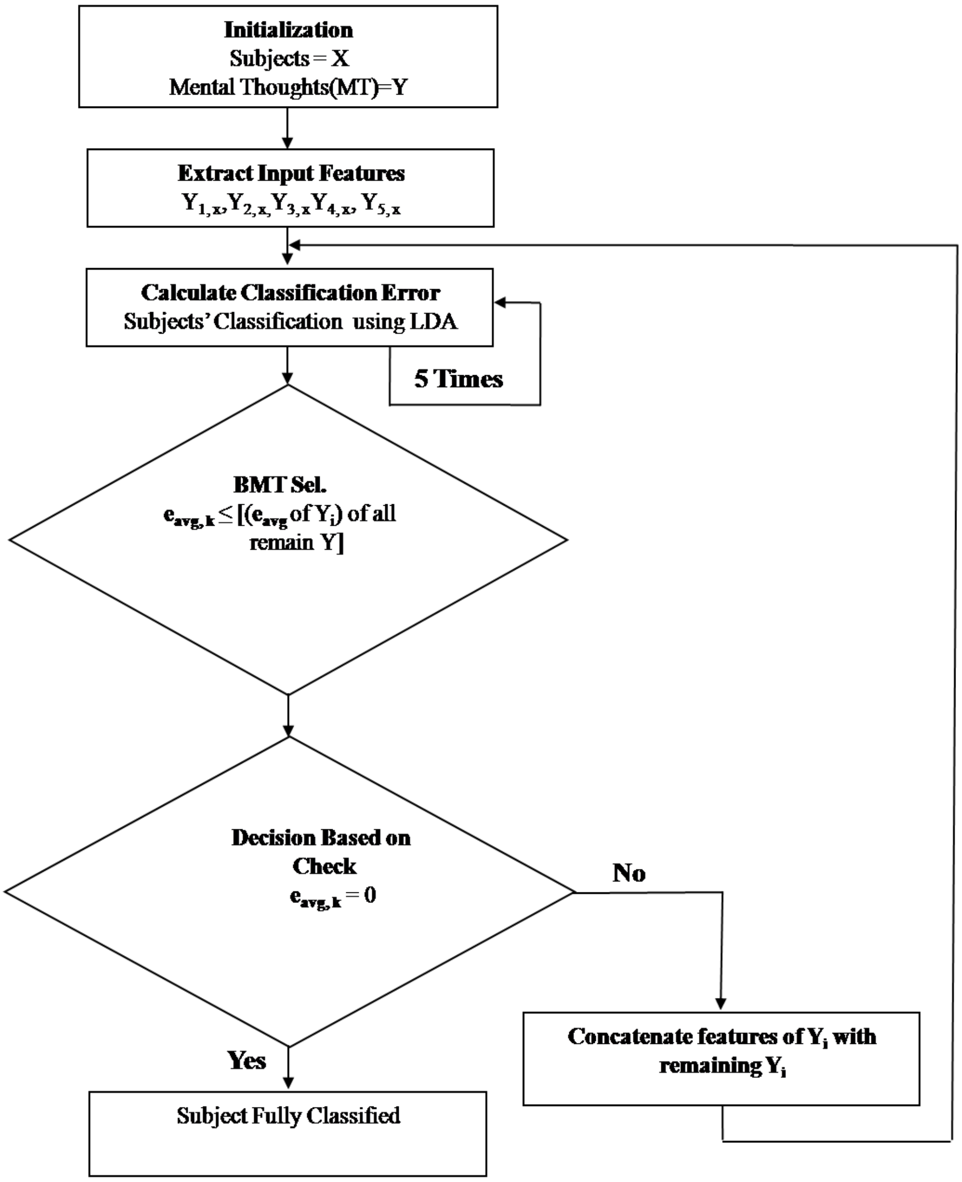

Figure 2. Flow chart for efficient classification algorithm.

average classification error of the proposed algorithm reduced as compared to the results of [14]. The processing time of 4 combinations reduces to 310 µs, whereas, possible combinations of two mental thoughts in [14] requires a processing time of 775 µs. As the average classification error of multiplication-letter combination is minimum, so it is selected as a two BMT for further processing. The possible combinations for three mental thoughts using two BMT reduced to 3 from 10 as well as the processing time reduced to 465 µs from 1550 µs as described in [14]. Table 1 shows that minimum average classification error for three BMT combinations is 0.05%, hence three BMT combination will be multiplication, letter and baseline. As, the average classification error is still not equal to 0% so two combinations of four mental thoughts are processed to evaluate the average classification error and so on, till the average classification error reaches to 0% for declaring the individual to be fully classified. The overall processing time required to fully classify an individual using efficient classification algorithm based on BMT is 1.44 ms. The processing time of 1.44 ms can easily be achieved because of available fast computing processor & machine.

Table 1. Comparative analysis of classification error and processing between R. Palaniappan Method [14] and efficient classification algorithm.

R. Palaniappan Method [14]					Efficient Classification Algorithm				
Mental Thoughts	**% classification error**			**Processing Time**	**Mental Thoughts**	**% classification error**			**Processing Time**
	Min	**Max**	**Avg.**			**Min**	**Max**	**Avg.**	
Baseline	6	7.125	6.625	40 μs	Baseline	6.25	7.125	6.625	40 μs
Counting	3.75	5.25	4.875	40 μs	Counting	3.75	5.25	4.95	40 μs
Letter	5.875	6.875	6.35	40 μs	Letter	5.875	6.625	6.275	40 μs
Multiplication	**2.125**	**3**	**2.675**	**40 μs**	**Multiplication**	**2.125**	**3.125**	**2.725**	**40 μs**
Rotation	4.875	5.5	5.2	40 μs	Rotation	4.875	5.5	5.2	40 μs
Processing Time for One Mental Thought				**200 μs**	**Processing Time for One Mental Thought**				**200 μs**
Best Mental Thought: Multiplication					**Best Mental Thought: Multiplication**				
Baseline, Counting	0.5	0.875	0.725	77.5 μs	Multiplication, Baseline	0.75	1	**0.825**	**77.5 μs**
Baseline, Letter	1	1.25	1.125	77.5 μs	Multiplication, Counting	0.75	0.875	**0.8**	**77.5 μs**
Multiplication, Letter	**0.5**	**0.625**	**0.6**	**77.5 μs**	**Multiplication, Letter**	**0.375**	**0.75**	**0.6**	**77.5 μs**
Baseline, Rotation	0.875	1.625	1.425	77.5 μs	Multiplication, Rotation	0.875	1.25	**1..05**	**77.5 μs**
Letter, Counting	0.5	1.5	1.325	77.5 μs					
Letter, Rotation	0.75	0.87	0.825	77.5 μs					
Multiplication, Counting	0.75	0.875	0.8	77.5 μs					
Baseline, Multiplication	0.75	1	0.875	77.5 μs					
Multiplication, Rotation	0.875	1.25	1.1	77.5 μs					
Rotation, Counting	0.375	1.25	1.05	77.5 μs					
Processing Time for Two Mental Thought				**775 μs**	**Processing Time for Two Mental Thought**				**310 μs**
Best Mental Thought: Multiplication, Letter					**Best Mental Thought: Multiplication, Letter**				
Baseline, Letter, Counting	0.25	0.5	0.375	155 μs	Multiplication, Letter, Counting	0	0.25	0.1	**155 μs**
Multiplication, Letter, Baseline	**0**	**0.125**	**0.05**	**155 μs**	**Multiplication, Letter, Baseline**	**0**	**0.25**	**0.05**	**155 μs**
Multiplication, Baseline, Counting	0.125	0.25	0.2	155 μs	Multiplication, Letter, Rotation	0.25	0.375	0.325	**155 μs**
Letter, Counting, Multiplication	0	0.25	0.1	155 μs					

Cont….

R. Palaniappan Method [14]					**Efficient Classification Algorithm**				
Mental Thoughts	**% classification error**			**Processing Time**	**Mental Thoughts**	**% classification error**			**Processing Time**
	Min	**Max**	**Avg.**			**Min**	**Max**	**Avg.**	
Rotation, Baseline, Counting	0.175	0.75	0.55	155 μs					
Rotation, Baseline, Letter	0.125	0.375	0.225	155 μs					
Rotation, Letter, Counting	0	0.25	0.125	155 μs					
Rotation, Multiplication, Baseline	0.375	0.625	0.45	155 μs					
Rotation, Multiplication, Counting	0.25	0.375	0.325	155 μs					
Rotation, Multiplication, Letter	0.25	0.375	0.3	155 μs					
Processing Time for Three Mental Thought				**1550 μs**	**Processing Time for Three Mental Thought**				**465 μs**
Best Mental Thought: Multiplication, Letter, Baseline					**Best Mental Thought: Multiplication, Letter, Baseline**				
Multiplication, Letter, Counting, Baseline	0	0.125	0.05	235 μs	Multiplication, Letter, Baseline, Counting	0	0.125	0.05	235 μs
Multiplication, Letter, Baseline, Rotation	**0**	**0**	**0**	**235 μs**	**Multiplication, Letter, Baseline, Rotation**	**0**	**0**	**0**	**235 μs**
Rotation, Multiplication, Baseline, Counting	0.125	0.25	0.15	235 μs					
Rotation, Multiplication, Counting, Letter	0	0.125	0.055	235 μs					
Rotation, Baseline, Letter, Counting	0	0.125	0.075	235 μs					
Processing Time for Four Mental Thought				**1175 μs**	**Processing Time for Four Mental Thought**				**470 μs**
Best Mental Thought: Multiplication, Letter, Baseline, Rotation					**Best Mental Thought: Multiplication, Letter, Baseline, Rotation**				
Rotation, Baseline, Letter, Count, Multiplication	0	0	0	390 μs					
Over all Processing Time				**4.1 ms**	**Overall Processing Time**				**1.44 ms**

5. Conclusion

In this research work, an efficient classification algorithm based on BMT is proposed to classify individual using their brain signals (EEG). The classification error reduces as the number of mental thoughts increases while the overall system complexity and processing time increases and vice versa. The proposed efficient classification algorithm reduces the complexity (in term of number of possible combinations reduction) as well as processing time by selecting best mental thought among multiple mental thoughts.

Combinations of selected BMT are formed for multiple mental thoughts instead of forming all possible combinations which reduces the systems complexity and possible combinations of multiple mental thoughts as well.

Acknowledgement

We would like to acknowledge Mr. Inam-ur-Rehman, Lecturer, Department of Electrical Engineering, Wah Engineering College, Pakistan for his valuable suggestions throughout this research work and www.cs.colostate.edu/eeg/ eegSoftware.html#keirndat for the availability of data for further processing.

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