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Multiple Mental Thought Parametric Classification: A New Approach for Individual Identification

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***Abstract*—**This paper reports a new approach on identifying the individuality of persons by using parametric classification of multiple mental thoughts. In the approach, electroencephalogram (EEG) signals were recorded when the subjects were thinking of one or more (up to five) mental thoughts. Autoregressive features were computed from these EEG signals and classified by Linear Discriminant classifier. The results here indicate that near perfect identification of 400 test EEG patterns from four subjects was possible, thereby opening up a new avenue in biometrics.

***Keywords*—**Autoregressive, Biometrics, Electroencephalogram, Linear discrimination, Mental thoughts.

I. Introduction

THERE are several biometrics that are actively used for identification of individuals. The most common of these is fingerprints [8, 12]. However, the individuality of fingerprints, i.e. whether it is unique to an individual has been challenged [8]. Therefore, it becomes important to find alternative biometric methods to replace or augment the fingerprint technology especially with regards to increased security requirements to combat terrorism. In this regard, other biometrics like speech, iris, face [12], palmprint [2], hand geometry [4], electrocardiogram [1], electroencephalogram (EEG) [9, 10] and visual evoked potential (VEP) [6] have been proposed.

However, using EEG as a biometric is relatively new as compared to the other biometrics. Poulus et al [10] proposed a method using autoregressive (AR) modelling of EEG signals and Learning Vector Quantization to classify an individual as distinct from other individuals with 72-80% success. But the method was not tried to recognise each individual in a group. Paranjape et al [9] used AR modelling of EEG with discriminant analysis to identify individuals with classification accuracy ranging from 49 to 85%. Palaniappan [6] proposed using VEP (i.e. stimulus evoked EEG) recorded while the individuals perceive a single picture. However, this method required 61 channels, which is cumbersome and also required the individuals to perceive a visual stimulus, which is drawback for the visually impaired.

In previous papers, it has been shown that mental thoughts classification is a suitable technique for use in the design of Brain Computer Interfaces (BCIs) to aid the disabled to communicate or control devices [5, 7]. BCIs are also useful for hands-off menu activation, which could be used by anyone. In this paper, mental thoughts are proposed for a different application: to identify the individuality of persons. As far as the knowledge of the author is concerned, this is novel when used for biometrics.

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II. Data

The EEG data used in this study were collected by Keirn and Aunon [5] for their BCI experiments. Data from four subjects were used in this study. The subjects were seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noise-less fan (for ventilation). An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 (shown in Figure 1), defined by the 10-20 system of electrode placement.

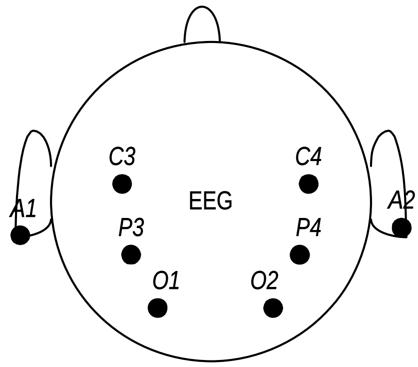

Fig. 1 Electrode placement

The impedances of all electrodes were kept below 5 KΩ. Measurements were made with reference to electrically linked mastoids, A1 and A2. The electrodes were connected through a bank of Grass7P511 amplifiers, whose band-pass analog filters were set at 0.1 to 100 Hz. The data were sampled at 250

Hz with a Lab Master 12-bit A/D converter mounted on a computer. Before each recording session, the system was calibrated with a known voltage.

Signals were recorded for 10s during each task and each task was repeated for 10 sessions where the sessions were held on different weeks. The EEG signal for each mental thought was segmented into 20 segments with length 0.5 s. The sampling rate was 250 Hz, so each EEG segment was 125 data points (samples) in length.

In this paper, EEG signals from four subjects performing five different mental thoughts have been used. Keirn and Aunon [5] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). These mental thoughts were:

- Baseline task. The subjects were asked to relax and think of nothing in particular. This task was used as a control and as a baseline measure of the EEG signals.
- Geometric figure rotation task. The subjects were given 30 s to study a particular three-dimensional block object, after which the drawing was removed and the subjects were asked to visualize the object being rotated about an axis. The EEG signals were recorded during the mental rotation period.
- Math task. The subjects were given nontrivial multiplication problems, such as 79 times 56 and were asked to solve them without vocalizing or making any other physical movements. The tasks were non-repeating and designed so that an immediate answer was not apparent. The subjects verified at the end of the task whether or not he/she arrived at the solution and no subject completed the task before the end of the 10 s recording session.
- Mental letter composing task. The subjects were asked to mentally compose a letter to a friend or a relative without vocalizing. Since the task was repeated for several times the subjects were told to continue with the letter from where they left off.
- Visual counting task. The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were instructed not to verbalize the numbers but to visualize them. They were also told to resume counting from the previous task rather than starting over each time.

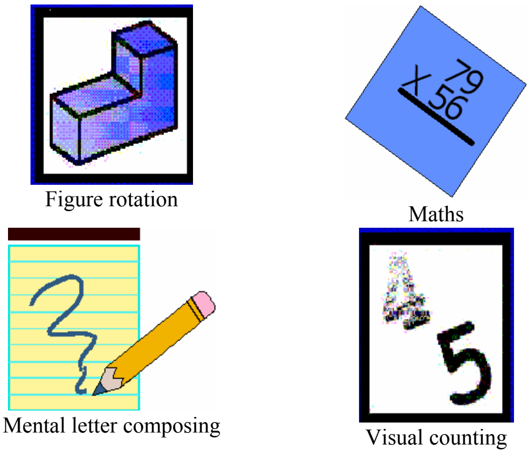

Fig. 2 The four active mental thoughts. The other mental thought was baseline. Note that the subjects imagined these activities without performing any form of action

III. AR Feature Extraction

The EEG signals were subjected to feature extraction using parametric AR modeling. A real valued, zero mean, stationary, AR process of order p is given by

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

where *p* is the model order, *x(n)* is the signal at the sampled point *n*, a_k are the real valued AR coefficients and *e(n)* represents the error term independent of past samples. The term autoregressive implies that the process *x(n)* is seen to be regressed upon previous samples of itself. The error term is assumed to be a zero mean noise with finite variance. In applications, the values of a_k have to be estimated from finite samples of data, *x(1), x(2), x(3), … ,x(N).*

In this paper, Burg's method [11] was used to estimate the AR coefficients. The method is more accurate as compared to other methods like Levinson-Durbin as it uses the data point directly. Furthermore, Burg algorithm uses more data points by minimizing both forward error and backward error.

In computing AR coefficients, order six was used because other researchers [5, 7] have suggested the use of order six for AR process for mental thought classification. Therefore, six AR coefficients were obtained for each channel, giving a total of 36 feature vector for each EEG segment for a mental thought. When two mental thoughts were used, the size of the feature vector was 72 and so forth when more mental thoughts were used.

IV. Linear Discriminant Classifier

Linear Discriminant Classifier (LDC) [3] is a linear classification method that is computationally attractive as compared to other classifiers like artificial neural network. It could be used to classify two or more groups of data. Here, LDC was used to classify the EEG feature vectors into one of the four categories representing the subject.

In principle, any mathematical function may be used as a classifier function. In case of the LDC as used here, the EEG training feature vectors were used to derive the classification functions as

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

where x_i is the set of AR coefficients from the EEG feature vectors, N is 32, 72, 108, 144 or 180 depending on the number of mental thoughts used, w_i and a are the coefficients and constant, respectively. The functions would be formed in such a way that the separation (i.e. distance) between the groups was maximized, and the distance within the groups was minimized i.e. the parameters w_i and a would be determined in such a way that the discrimination between the groups was best. Using these classification functions, the discriminant scores of each test EEG feature vector occurring in each of the groups were computed. The test EEG feature vector was then assigned to the group with the highest score and then compared with the actual class to determine the classification error.

A total of 800 EEG feature vectors (20 segments for EEG each signal x 10 sessions x 4 subjects) were used in the experimental study. Half of the patterns were used in training and the remaining half in testing. The selection of the patterns for training and testing were chosen randomly. A modified 10 fold cross validation procedure was used to increase the reliability of the results. In this procedure, the entire data for an experiment (i.e. 800 EEG feature vectors) were split into 10 parts, with equal number of feature vectors from each subject. Training and testing were repeated for five times where for each time, five different parts were used for training and the remaining five parts for testing. This was done to increase the reliability of the classification results.

V. Results and Discussion

Tables I-V show the classification results using the modified 10 fold cross-validation scheme. As each classification experiment (training and testing) was repeated five times, the minimum, maximum and average of the five classification errors are reported in the tables. It could be seen clearly that the classification error drops as more mental thoughts were used. This is as anticipated as more mental thoughts would increase the inter-subject variance of the AR features. The lowest error for a single mental thought was given by the maths task, with the average error of 2.60%, while for five mental thoughts; the average error was only 0.1%.

TABLE I
RESULTS WITH MODIFIED 10 FOLD CROSS-VALIDATION USING ONE MENTAL THOUGHT

	Classification error (%)		
Mental thoughts	Min	Max	Average
Baseline	6.00	10.0	7.55
Count	3.25	7.00	4.70
Letter	6.00	8.75	7.55
Maths	1.50	3.75	2.60
Rotation	4.50	7.50	5.70
Overall average	4.25	7.40	5.62
Minimum	1.50	3.75	2.60
Best mental thought (using average value): Maths			

The increase in recognition accuracy that follows the higher number of mental thoughts results in more complexity and computational time. The increase in computational time is insignificant especially with the easy availability of fast computing power. The computational times required were approximately 40 μs, 77.5 μs, 155 μs, 235 μs and 390 μs for one, two, three, four and five mental thoughts, respectively. The increase in complexity is a cause for concern but the method is simple as the subjects have to think of the different mental thoughts only, which could be easily mastered with some training.

TABLE II
RESULTS WITH MODIFIED CROSS-VALIDATION USING TWO MENTAL THOUGHTS

	Classification error (%)		
Mental thought combinations	Min	Max	Average
Baseline, Count	0.75	3.50	1.50
Baseline, Letter	1.25	2.25	1.50
Baseline, Maths	0.75	1.50	1.05
Baseline, Rotation	0.75	3.00	1.85
Letter, Count	0	2.75	1.25
Letter, Rotation	1.00	2.25	1.40
Maths, Count	0.75	2.00	1.10
Maths, Letter	0.25	2.00	0.95
Maths, Rotation	0.50	1.50	1.15
Rotation, Count	0.25	3.50	1.65
Overall average	0.63	2.43	1.34
Minimum	0	1.50	0.95
Best mental thought combination (using average value): Maths, Letter			

With the use of electrode caps, the placement of the six electrodes will not be cumbersome and a simple hat that fits most heads could be designed. If necessary, the EEG signals could be transmitted wirelessly to the computer for processing. As mentioned, the computational time for feature extraction and classification for a single EEG feature vector of 390 μs for the case of using five mental thoughts is low. Combined with the 2.5 s required for five mental thoughts, the time required for the operation of the system is feasible to be implemented.

TABLE III
RESULTS MODIFIED 10 FOLD CROSS-VALIDATION USING THREE MENTAL THOUGHTS

	Classification error (%)		
Mental thought combinations	Min	Max	Average
Baseline, Letter, Count	0.25	1.75	0.75
Letter, Count, Maths	0	1.25	0.50
Maths, Baseline, Count	0	2.00	0.55
Maths, Baseline, Letter	0	0.50	0.20
Rotation, Baseline, Count	0	2.25	0.90
Rotation, Baseline, Letter	0	1.00	0.50
Rotation, Letter, Count	0	2.00	0.55
Rotation, Maths, Baseline	0.50	1.50	0.85
Rotation, Maths, Count	0.25	2.50	1.00
Rotation, Maths, Letter	0	1.25	0.45
Overall average	0.10	1.60	0.63
Minimum	0	0.50	0.20
Best mental thought combination (using average value): Maths, Baseline, Letter			

TABLE IV
RESULTS WITH MODIFIED CROSS-VALIDATION USING FOUR MENTAL THOUGHTS

	Classification error (%)		
Mental thought combinations	Min	Max	Average
Maths, Letter, Count, Baseline	0	1	0.3
Rotation, Baseline, Letter, Count	0	0.75	0.35
Rotation, Maths, Count, Baseline	0	1.75	0.55
Rotation, Maths, Count, Letter	0	0.75	0.35
Rotation, Maths, Letter, Baseline	0	0.5	0.1
Overall average	0	0.95	0.33
Minimum	0	0.5	0.1
Best mental thought combination (using average value): Rotation, Maths, Letter, Baseline			

TABLE V
RESULTS WITH MODIFIED CROSS-VALIDATION USING FIVE MENTAL THOUGHTS

	Classification error (%)		
Mental thought combination	Min	Max	Average
Rotation, Maths, Count, Letter, Baseline	0	0.5	0.1

VI. CONCLUSION

In this paper, a novel method of identifying individuals using classification of feature vectors from EEG signals recorded during mental thoughts has been proposed as a biometric tool. The features consisted of sixth order AR values computed from six EEG channels that were recorded while the subjects thought of different mental thoughts. LDC was used to classify the EEG feature vectors, where a modified 10 fold cross validation procedure was used to improve the reliability of the results. The near perfect classification over 400 test EEG feature vectors from four subjects show promise for the method to be studied further as a biometric for individual identification. The method could be used as a uni-modal (stand alone) or in part of a multi-modal individual identification system and is mainly advantageous because of the difficulty in establishing another persons exact EEG output. However, the changes of EEG patterns over longer periods of time need to be investigated.

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