Identifying Individuality Using Mental Task Based Brain Computer Interface

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Abstract

In recent years, numerous Brain Computer Interface (BCI) technologies have been developed to assist the disabled. In this paper, mental task based BCI is proposed for a different purpose: to identify the individuality of a person. The idea is based on the classification of electroencephalogram (EEG) signals recorded when a user thinks of either one or two mental tasks. As different individuals have different thought processes, this idea would be appropriate for individual identification. To increase the inter-subject differences, EEG data from six electrodes are used instead of one. Sixth order autoregressive features are computed from EEG signals and classified by Linear Discriminant classifier using a modified 10 fold cross validation procedure, which gave an average error of 0.95% when tested on 400 EEG patterns from four subjects. Though the method would have to undergo further development to obtain repeatable good accuracy; this initial study has shown the huge potential of the method over existing biometric identification systems as it is impossible to be faked.

1. Introduction

The most common biometric method of identifying an individual is through fingerprint recognition [1,2]. However, the individuality of fingerprints has been challenged [2]. Therefore, it becomes important to find alternative biometric methods to replace or augment the fingerprint technology. In this regard, other biometrics like palmprint [3], hand geometry [4], iris [5], face [6], and electrocardiogram [7] have been proposed.

However, using EEG as a biometric is relatively new as compared to the other biometrics. Poulus *et al* [8] proposed a method using autoregressive (AR) modelling of EEG signals and Linear Vector Quantisation (LVQ) NN 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 [10] proposed using Visual Evoked Potential 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 task classification is a suitable technique for use in the design of Brain Computer Interfaces (BCIs) to aid the disabled to communicate or control devices [11-13]. BCIs are also useful for hands-off menu activation, which could be used by anyone. In this paper, mental task based BCI is proposed for a different application: to identify the individuality of the subjects. As far as the knowledge of the author is concerned, this is a novel BCI application.

2. Data

The EEG data used in this study were collected by Keirn and Aunon [11]. 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 [14] of 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 amplifiers (Grass7P511), 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.

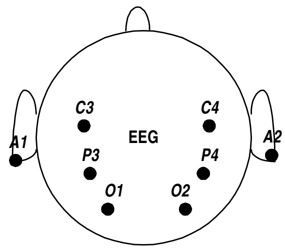

Fig. 1: Electrode placement

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 task 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 tasks have been used. The data is available online at http://www.cs.colostate.edu/~anderson. These mental tasks were:

a) 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.
b) Math task. The subjects were given nontrivial multiplication problems, such as 42 times 18 and were asked to solve them without vocalising 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.
c) 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 visualise the object being rotated about an axis. The EEG signals were recorded during the mental rotation period.
d) Mental letter composing task. The subjects were asked to mentally compose a letter to a friend or a relative without vocalising. Since the task was repeated for several times the subjects were told to continue with the letter from where they left off.
e) Visual counting task. The subjects were asked to imagine a blackboard and to visualise 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 verbalise the numbers but to visualise them. They were also told to resume counting from the previous task rather than starting over each time.

Keirn and Aunon [11] specifically chose these tasks since they involve hemispheric brainwave asymmetry (except for the baseline task). For example, it was shown by Osaka [15] that arithmetic tasks exhibit a higher power spectrum in the right hemisphere whereas visual tasks do so in the left hemisphere. As such, Keirn and Aunon [11] and later Anderson *et al* [12] proposed that these tasks are suitable for brain-computer interfacing.

3. FEATURE EXTRACTION AND CLASSIFICATION

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

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

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 $x(1), x(2), x(3), \ldots ,x(N)$.

In this paper, Burg's method [16] 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 minimising both forward error and backward error. The Burg algorithm is given in the appendix.

In computing AR coefficients, order six was used because other researchers [11-13] have suggested the use of order six for AR process for mental task classification. Therefore, six AR coefficients were obtained for each channel, giving a total of 36 feature vector for each EEG segment for a mental task. When two mental tasks were used, the size of the feature vector was 72.

4. LINEAR DISCRIMINANT CLASSIFIER

Linear Discriminant Classifier (LDC) [17] 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

$$F = \sum_{i=1}^{N} x_i w_i + a \ , \tag{2}$$

where x_i is the set of AR coefficients from the EEG feature vectors, N is 32 or 72 depending on whether a single mental task was used or a pair of mental tasks were 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 VEP 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.

5. RESULTS AND DISCUSSION

Table 1 shows the classification results (in terms of percentage error) using one mental task, while Table 2 shows the classification results using combination of two mental tasks. The results were obtained using the modified 10 fold cross validation procedure mentioned earlier. The maximum, minimum and average of the five repeated experiments using the modified 10 fold cross validation procedure are reported in the Tables. From Table 1, the best mental task that discriminated the subjects was maths task, while from Table 2, it could be seen that the best combination of mental task pairs was Maths-Letter (using the values in the average column). There was a reduction in classification error by using the mental task pairs instead of a single mental task. In future experiments, it is planned to increase the number of mental tasks to further reduce the classification error.

TABLE 1: RESULTS WITH MODIFIED 10 FOLD CROSS-VALIDATION USING ONE MENTAL TASK

	Classification error (%)		
Mental task	**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 task	Maths	Maths	Maths

The method is simple as the subjects have to think of the mental tasks only, which could be easily mastered with some training. With the use of electrode caps, the placement of 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. The computational time for feature extraction and classification for a single EEG feature vector was approximately 40 μs for the case of using a single mental task and 80 μs for the case when a pair of mental tasks was used. Combined with the 0.5 s required for a single mental task and 1.0 s for the pair of mental tasks, the time required for the operation of the system is feasible for to be implemented. However, the changes of EEG patterns over longer periods of time need to be investigated.

TABLE 2: RESULTS WITH MODIFIED 10 FOLD CROSS-VALIDATION USING TWO MENTAL TASKS

	Classification error (%)		
Mental task combination	**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	0.00	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	0.00	1.50	0.95
Best mental task combination	Letter, Count	Baseline,Maths Maths,Rotation	Maths, Letter

6. CONCLUSION

In this paper, a novel method of identifying individuals using classification of feature vectors from EEG signals recorded during mental tasks has been proposed as a biometric tool. The features consist of sixth order AR values computed from six EEG channels that are recorded while the subjects think of different mental tasks. 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 average classification error of 0.95% over 400 test EEG feature vectors from four subjects show promise for the method to be studied further as a biometric tool 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.

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Appendix – Burg's algorithm

Step 1:

Initial conditions:

$$\hat{\pi}_0 = r(0)$$

The forward prediction errors, $\varepsilon_0^f(n) = y(n)$, where n = 1, 2, 3, …, N-1

The backward prediction errors, $\varepsilon_0^b(n) = y(n)$, where n = 0, 1, 2, …, N-2

N is the data size.

Step 2:

Reflection coefficients. For p = 1, 2, 3, …, P, where P is the required model order

$$\hat{\pi}_p = \frac{-2\sum_{n=p}^{N-1}\varepsilon_{p-1}^f(n)\varepsilon_{p-1}^b(n-1)}{\sum_{n=p}^{N-1}\{[\varepsilon_{p-1}^f(n)]^2 + [\varepsilon_{p-1}^b(n-1)]^2\}} \quad \text{(A.1)}$$

$$s_p^2 = (1 - \left|\hat{\pi}_p\right|^2)s_{p-1}^2 \quad \text{(A.2)}$$

For p = 1,

$$\hat{a}_1(1) = \hat{\pi}_1$$

For p > 1,

$$a_p(i) = \begin{cases} a_{p-1}(i) + \hat{\pi}_p\, a_{p-1}(p-i) & \text{for} \quad i = 1,2,3,\ldots p-1 \\ \hat{\pi}_p & \text{for} \quad i = p \end{cases} \quad \text{(A.3)}$$

Step 3:

Prediction errors for next orders:

$$\varepsilon_p^f(n) = \varepsilon_{p-1}^f(n) + \hat{\pi}_p\, \varepsilon_{p-1}^b(n-1),$$

(A.4)

for n = k+1, k+2, …, N-1

$$\varepsilon_p^b(n) = \varepsilon_{p-1}^b(n-1) + \hat{\pi}_p\, \varepsilon_{p-1}^f(n),$$

(A.5)

for n = k+1, k+2, …, N-2

Note: k = the first n in the previous step to determine errors

Step 4:

Repeat step 2 and 3 (with p incremented by 1) until the selected model order p is reached.