PIN Generation Using Single Channel EEG Biometric

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Abstract. This paper investigates a method to generate personal identification number (PIN) using brain activity recorded from a single active electroencephalogram (EEG) channel. EEG based biometric to generate PIN is less prone to fraud and the method is based on the recent developments in brain-computer interface (BCI) technology, specifically P300 based BCI designs. Our perfect classification accuracies from three subjects indicate promise for generating PIN using thought activity measured from a single channel.

Keywords: Biometrics, Brain computer interface, Electroencephalogram, Information transfer rate, Neural networks.

1 Introduction

Biometric technologies can be roughly divided into those that that identify a person or authenticate a person's identity [1]. Personal identification number (PIN) is one commonly used 'confidential sequence of numerals' to authenticate a person's identity, as employed in automated teller machine (ATM) to withdraw cash or perform other functions. In recent years, PINs have been used to authenticate debit and credit cards in lieu of signatures. In this paper, we investigate a method to generate PIN using only brain's electrical activity (i.e. electroencephalogram (EEG)). The advantage is obviously that it is less prone to fraud such as shoulder surfing problem as in the conventional method of keying in the numbers.

The method follows the recent developments in brain-computer interface (BCI) technology [2]. BCI designs were initially developed to assist the disabled to communicate with their external surroundings as they circumvent the peripheral nerves and muscles to create a link between the brain and computers/devices. In recent years, BCI designs have been explored for other purposes such as biometrics [3, 4], games design [5], virtual reality [6] and robotics [7].

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There are many BCI paradigms, the most common being the non-invasive EEG based. EEG based BCI designs could be further divided into those based on transient evoked potential, motor imagery, slow cortical potential, mental task and steady state evoked potential. Transient evoked potential method, more commonly known as the P300 method as it is based on a potential that is generated about 300-600 ms after the stimulus onset, is probably the method chosen by many BCI researchers due to its simplicity and ease of use by the subjects. The thought based PIN generation investigated here is based on this P300 based BCI.

2 Methodology

Three right handed male subjects aged 24 participated in this study. The objective of the experiment and the description of the experiment were given to the subjects before they signed a voluntary consent. The experiment was approved by the University of Essex's Ethics Committee. The subjects were seated in a room with computer screen projected about 30 cm from their eyes. The subjects had no uncorrected visual problems. The visual stimulus paradigm is as shown in Figure 1.

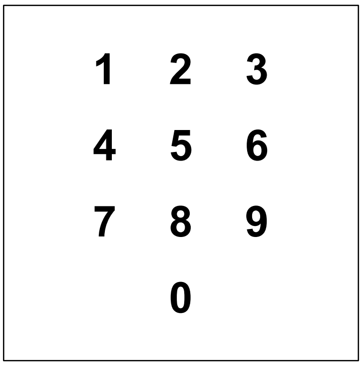

Fig. 1. Visual stimulus paradigm

The numbers on the screen were flashed randomly with each flash lasting 100 ms with 75 ms inter-stimulus interval (ISI). These timings were chosen from a previous study [7]. The subjects were asked to concentrate on a given target number and to keep a mental count of the target flashes (this is to avoid lapses of concentration). When a target number is flashed, a positive potential about 300-600 ms after stimulus onset in evoked and shows up in the recorded EEG signal. A total of five trials were conducted in each session where a trial consisted of ten random flashes of each number. A short break of 2.5 s was given between each session. A second session was conducted on a separate week. EEG data from 32 electrodes as shown in Figure 2 was collected using Biosemi Active Two system. The sampling rate used was 256 Hz. One second EEG data after stimulus onset from each flash was extracted for further processing.

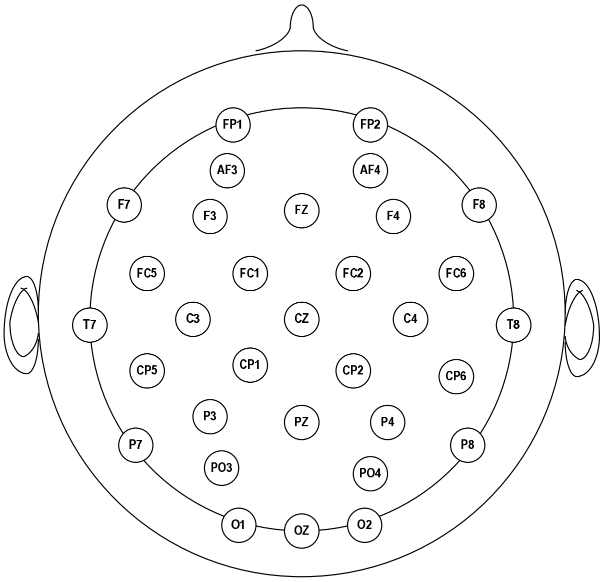

Fig. 2. Used electrode locations

2.1 Pre-processing

The data was bandpass filtered using a Butterworth IIR filter with order 6. Two commonly used bandpass ranges of 1-8 Hz [9] and 1-12 Hz [10] were used. Next, the data was downsampled to 32 samples. Windsorising as suggested in [10] was applied to remove outlier data beyond 10^{th} and 90^{th} percentiles. A single hidden layer feed-forward neural network classifier trained by the backpropagation algorithm was used to train and test the performance of the processed EEG data.

2.2 Classification

Instead of treating the classification as a ten class problem, the classifier was trained with only two outputs, one for target and another for non-target. Our preliminary simulations show that the results are much improved following this strategy. Data from one session was used to train the neural network while the remaining data from the other session was used to test the performance of the classifier. To avoid overtraining the neural network with more non-target instances as compared to target instances, all 50 target instances (ten numbers x five flashes) were used with 50 randomly chosen non-target instances rather than the total 450 non-target instances. The training was conducted until mean square error fell below 0.0001 or a maximum iteration number of 1000 was reached. The hidden layer size was fixed to be similar to the number of inputs. For example, when 32 channels were used, the size was 1024.

The two outputs of the classifier were added incrementally after each trial. As the neural network could predict more than a single target for each trial, the maximal output after considering all the ten flashes in a trial was taken as the predicted target.

The classification step was repeated ten times (to reduce effects of different neural network weight connections) and also cross validated with the training and testing datasets swapped and performances from these 20 runs were averaged. All the computer simulations were conducted with MATLAB.

3 Results

Figure 3 shows the grand averaged 1-8 Hz bandpass filtered EEG response from 50 target and 50 non-target EEG signals for a subject. The occurrence of P300 component around 300-600 ms for the target flash (shown in red) as compared to non-target (shown in blue) is evident from the figure.

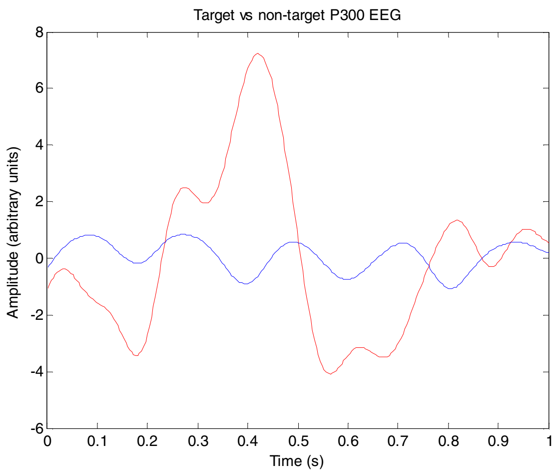

Fig. 3. Grand averaged EEG response for a subject

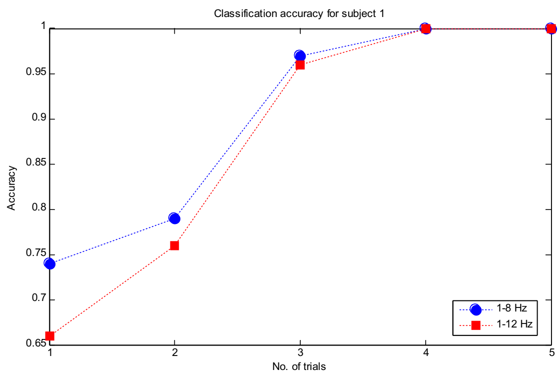

Fig. 4. Passband range comparison for subject 1

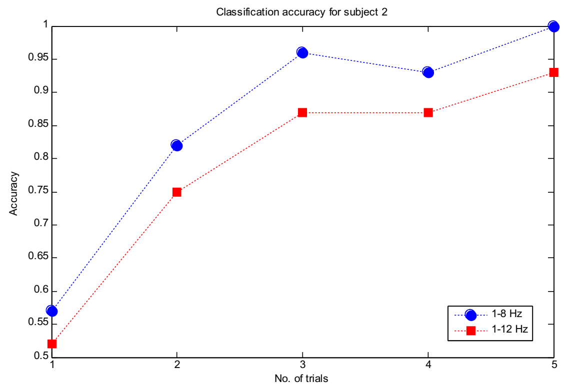

Fig. 5. Passband range comparison for subject 2

Figures 4-6 shows the results from subjects using all 32 channels with passband ranges of 1-8 Hz and 1-12 Hz. Passband range of 1-8 Hz gave improved performance (statistically significant, $p<0.1$) compared to passband range of 1-12 Hz for subjects 1 and 3 when considering the first two trials. For subject 2, 1-8 Hz range gave improved performance for all the trials. In the figures, accuracy value of 1.00 indicates perfect classification (i.e. 100%).

Tables 1-3 shows the results comparing the performance using 1 channel, 4 channels, 8 channels, 16 channels and all 32 channels with passband range of 1-8 Hz (passband range of 1-12 Hz was dropped from further analysis due to its poorer performance for all the subjects). The locations of multi-channels were obtained from [10] and are shown in Table 4, while our own preliminary simulations indicated location Cz to be the most favourable single channel.

The results indicate that perfect classification was obtained after five trials for all the subjects for all the channel configurations. Hence, using a single channel Cz would be sufficient if five trials were considered.

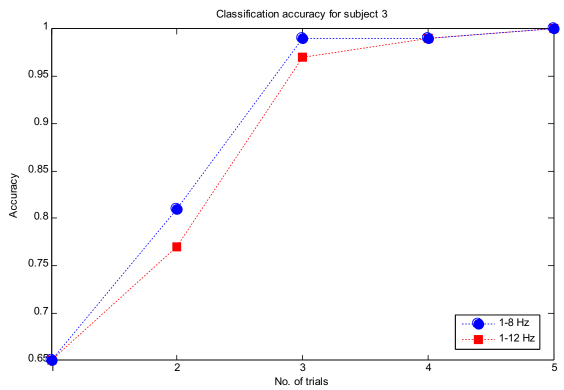

Fig. 6. Passband range comparison for subject 3

Table 1. Channel wise accuracy for subject 1

Channel/trial	1	2	3	4	5
1	0.56	0.67	0.84	0.95	1.00
4	0.66	0.74	0.83	0.96	1.00
8	0.71	0.71	0.93	1.00	1.00
16	0.74	0.81	0.97	1.00	1.00
32	0.74	0.79	0.97	1.00	1.00

Table 2. Channel wise accuracy for subject 2

Channel/trial	1	2	3	4	5
1	0.34	0.58	0.73	0.88	1.00
4	0.46	0.66	0.85	0.85	1.00
8	0.49	0.63	0.82	0.9	1.00
16	0.50	0.74	0.82	0.88	1.00
32	0.57	0.82	0.96	0.93	1.00

Table 3. Channel wise accuracy for subject 3

Channel/trial	1	2	3	4	5
1	0.58	0.77	0.73	0.85	1.00
4	0.55	0.63	0.79	0.93	1.00
8	0.62	0.73	0.92	1.00	1.00
16	0.67	0.8	0.97	1.00	1.00
32	0.65	0.81	0.99	0.99	1.00

Table 4. Channel locations

4 channels	Fz, Cz, Pz, Oz
8 channels	Fz, Cz, Pz, Oz, P7, P3, P4, P8
16 channels	Fz, Cz, Pz, Oz, P7, P3, P4, P8, O1, O2, CP1, CP2, C3, C4, FC1, FC2

Information transfer rate (ITR), which gives a measure of the performance based on the accuracy plus number of targets in bits/min was computed using [11]:

$$ITR = \log_2(N) + P\log_2(P) + (1-P)\log_2\left(\frac{1-P}{N-1}\right). \quad (1)$$

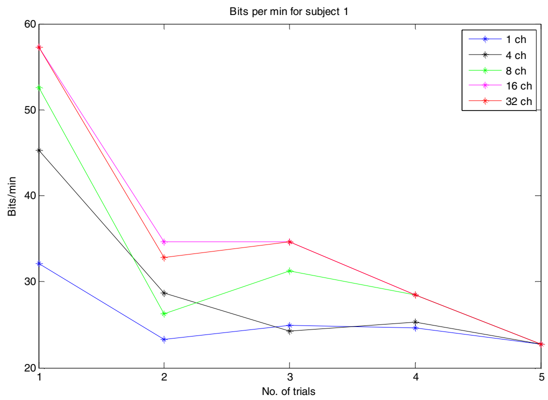

Fig. 7. ITR for subject 1

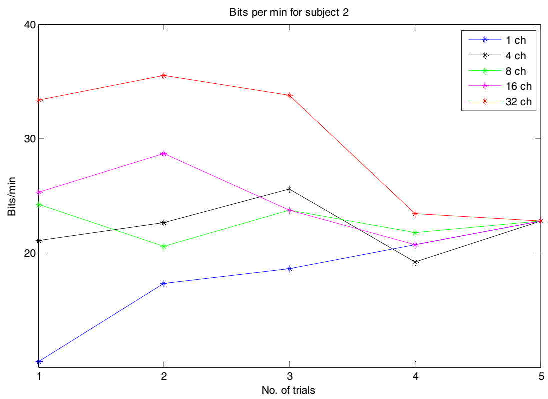

Fig. 8. ITR for subject 2

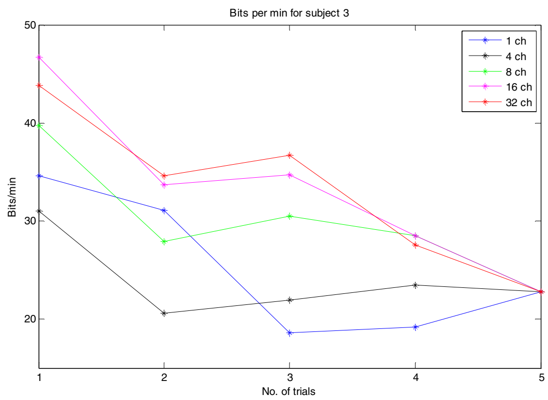

Fig. 9. ITR for subject 3

The ITR for each subject is shown in Figures 7-9 with passband range of 1-8 Hz. The best ITR of 57.29 bpm was obtained for subject 1 for 32 channels, which is much higher than reported in [10]. For single channel, this was 34.60 bpm for subject 3.

4 Conclusion

A method to generate PIN based on EEG signals has been investigated here. Major obstacle with EEG based biometric work is the cumbersome usage of many electrodes but our results indicate that single channel Cz with passband 1-8 Hz is appropriate for the investigated objective assuming a minimum of five trials. Furthermore, a reduction in the number of channels will reduce the cost, computational time and complexity. The perfect accuracy that is obtained after five trials shows the promise behind the method for fraud-resistant PIN generation. The design of the new capacitive electrodes will further remove the obstacle of having to use wet-EEG electrodes thereby bringing this method closer to deployment in the real world.

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