Single Trial P300 Amplitude for Pass-code Brain-Machine Interface Design

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ABSTRACT
In this pilot study, we design a pass-code Brain-Machine Interface (BMI) design using single trials of P300 amplitudes from Visual Evoked Potential (VEP) signals. The use of brain thought patterns as pass-codes is novel and is mainly advantageous since is the least likely to be compromised i.e. it is highly fraud resistant and would be suitable for use in environments where high security is essential such as access to confidential documents or locations. Here, we propose the use of colours as pass-codes due to their universality and the system would detect the colour focused by the user using electroencephalogram (EEG) signals recorded from the scalp. In addition, we also propose a simplification of the analysis by frequency specific filtering that allows single trial analysis as compared to ensemble averaging that is required in general to extract P300 components from EEG. Specifically, our averaged results of 72.15% indicate that the recognition performance of target colour stimuli in an oddball paradigm could be utilised for a biometrics BMI environment. Overall, the study shows that a single trial pass-code BMI design is possible, though the accuracy would need to be further improved for practical implementation and study with more subjects would be essential to establish the biometric usefulness.

Categories and Subject Descriptors
C.3 [**Computer system organizations**]: Special purpose and application-based systems – *signal processing systems.*

General Terms
Algorithms, Design, Security, Verification.

Keywords
Biometrics; Brain-Machine Interface; Genetic algorithm; P300; Visual Evoked Potential.

1. INTRODUCTION
Brain-machine Interface (BMI) designs are very useful for hands-off control and communication as they use the electrical activity of the brain to interface with the external environment, therefore circumventing the use of peripheral muscles and limbs [1].

There are two approaches to BMI designs namely invasive and non-invasive. The invasive designs though providing a better reliability and accuracy are not popular due to their invasiveness (for example, the use of electrodes implanted in the brain or sharp needles that penetrate the scalp).

Non-invasive designs could be divided into several categories based on the utilised signal; the common ones being electroencephalogram (EEG) and near-infra-red (NIR) where EEG based BMI designs are more established. EEG based BMI designs could be further divided into those based on Visual Evoked Potential (VEP) [2], mental activities [3], frequency following effect [4], motor imagery [5] and slow cortical potential [6].

There are several applications that are possible with EEG based BCI designs: assistive technology (locomotion, communication, neuro-prosthesis, game, bio-feedback, appliance control), neuro-diagnosis, and neuro-rehabilitation. The assistive technology BCI designs are very useful for partially or completely disabled individuals to perform actions such as controlling a wheelchair or to communicate with others. BCI designs are also very useful to rehabilitate muscles that have deteriorated or become damaged due to illness or accidents. The general public stands to benefit from BCI technology too in terms of gaming, bio-feedback and appliance control. In very recent times, a new application of BCI has emerged: for use as a biometric [7].

The goal of biometrics is to recognise or authenticate humans based on their physical and behavioral characteristics. The field of biometrics could be further divided into identification and authentication (i.e. verification of a claimed identity).

Identification of a person has become a much focused topic due to issues surrounding terrorism. Automatic personal verification or authentication of a user's individuality has also become an equally important issue for transaction especially with the advent of electronic banking and resources like computer log-in, automated teller machines, digital multimedia data access. It is especially very important in ensuring security for access to classified documents and highly restricted areas such as control gates in airports.

The most common biometric is the fingerprint [8]. An increasing number of fingerprint biometric systems have been witnessed, most typically in various government-run person identity databases. Despite its widespread use, fingerprints are not suitable for high security environments. Recent studies show that common household articles (e.g. gelatine) can be used to make artificial fingers and prints to bypass the security systems [9]. The other biometrics such as signature, face features, palmprint, hand geometry, iris and voice share similar a problem of easy forgery through some means or other.

This has motivated research on alternative biometrics [10]; these include approaches based on keyboard dynamics, ear force fields, heart signals, and odor but the fundamental issue of forgery that is still possible with these techniques have not been solved. This is where the usefulness of brain signal biometrics comes in; it is difficult to be forged.

2. CONTRIBUTIONS OF THE STUDY

In general, the VEP based BMI is the only method that does not require prior training and reliable accuracy could be obtained from naïve subjects. However, a difficulty with this method lies in the fact that it requires signal averaging from a number of trials. This is necessary as the important feature here is the P300 component and this component is often buried inside the ongoing EEG that is not related to the visual stimulus.

Methods based on principal component analysis [11] and independent component analysis [12] have been proposed to solve this problem. However, these methods are complex and time consuming and still require a few trials (though not as many as required for signal averaging method). This is a hurdle for real-time applications.

In this paper, we show that it is possible to design a single trial VEP based BMI by proper frequency specific filtering. It is known that P300 component is evoked during oddball paradigms, i.e. when a target object appears with lower occurrence amidst non-target objects [13]. Our results indicate that this component varies in terms of frequency responses and a suitable selection of the frequency range is important.

3. DATA

EEG data from a male subject aged 28 was used here. The data was recorded when the subject perceived seven different colours on white background that flashes on screen. The seven colours were (chosen randomly): Black, Red, Green, Blue, Yellow, Magenta and Cyan. The visual stimulus is shown in Figure 1.

Figure 1. Example of visual stimulus presentation.

The subject was instructed to focus on colours that randomly flashed on screen; a cue in the form of an asterisk was used to help the subject focus on the particular target colour. The objective would be to form a colour coded pass code generated by thought alone, which could be used to authenticate the identity of a person. For example, a passcode could be in the form of RED, GREEN, CYAN, BLACK, BLUE (sequence is important).

The flashes were intensified for 100 ms, with an inter-stimulus interval (ISI) of 300 ms. During the ISI, there would be no intensifications. The ISI is defined as the end of the intensification to the start of the next intensification. The period of 300 ms was chosen after some preliminary simulations.

Each colour would flash in random order until all colours have flashed; this is known as randomised block intensification. Each randomised block intensifications of 7 colours was considered as a trial. A blank period (i.e. without any intensification) of 2 seconds lasted between each trials. A total of 40 such trials were conducted.

The sampling frequency was 256 Hz and EEG data was recorded from 32 channels using Biosemi system. There were two channels: CMS and DRL that serves to make the recorded data as reference free. One second EEG data after each intensifications were stored. An example of EEG data from a trial is shown in Figure 2.

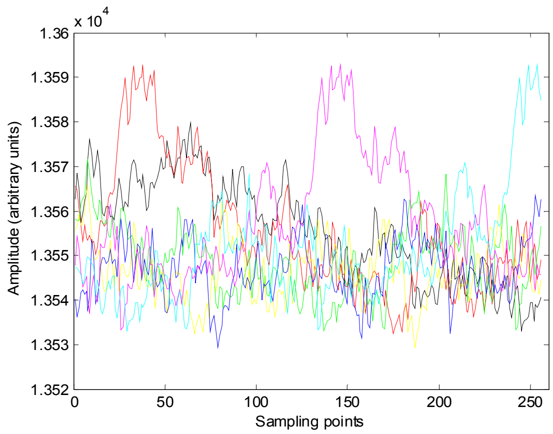

Figure 2. Raw EEG data from a trial.

4. EEG PROCESSING AND RESULTS

First, averages of left and right mastoid channels were used to re-reference the data. To extract P300 component, each EEG signal was low pass filtered to 8 Hz using a fourth order Elliptic Finite Impulse Response filter (with forward and reverse filtering to avoid phase distortion) and then normalised to zero mean and standard deviation of one. The cut-off frequency of 8 Hz was chosen after some preliminary simulations. Next, P300 amplitude was computed as the most positive peak in the range of 300-600 ms (or 77-154 sampling points) after stimulus onset. Figure 3 shows the processed EEG data.

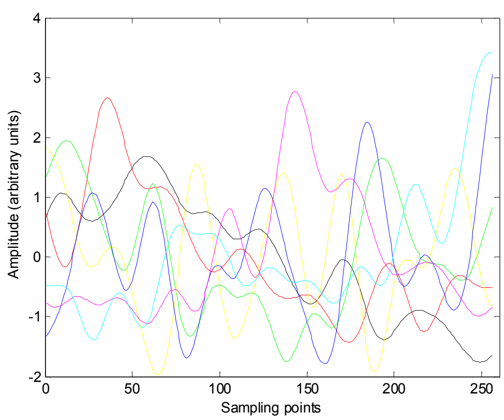

Figure 3. Processed EEG data from a trial.

For this pilot study, only channel Cz was used since it is known that P300 is maximal along midline [13]. Figure 4 shows the recognition results. Overall, the average recognition performance was 72.15%. It could also be seen from the figure that the best performance was obtained from colour red, probably due to the fact that this colour had a stronger attentive effect.

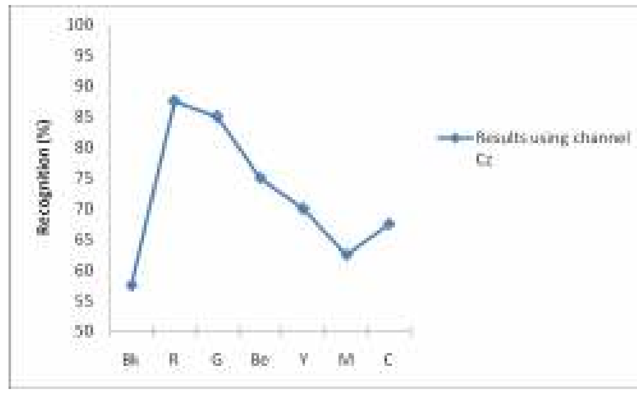

Figure 4. Recognition results showing recognition performance (%) for P300 amplitude from channel Cz. Legend: Bk –Black, R-Red, G-Green, Be-Blue, Y-Yellow, M-Magenta and C-Cyan.

5. CONCLUSION

Brain electrical activity has become the de facto standard in the diagnosis of brain related diseases, but there are very few reported studies on brain electrical activity based biometrics for both identification and authentication.

The only disadvantage of the BMI based biometric systems lies in the cumbersome data collection procedure but current improvements in data collection procedures (such as dry electrodes, instead of wet) will reduce the unwieldiness and that the fraud resistance significantly outweighs this difficulty especially for high security applications.

In this paper, single trial VEP based BMI design has been proposed. The method utilises P300 amplitude. Overall, the average recognition accuracy of 72.15% indicated that single trial classification of VEP based BMI design has potential to be developed as a biometric. The results obtained have shown the potential in applications such a stand alone biometric system or as a part of a multi-modal biometric system.

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