The Evolution of Non-Invasive Brain-Computer Interfaces

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ABSTRACT

The notion of solely using the human brain to interact with computers, without relying on the typical output pathways of peripheral nerves and muscles, is an enthusing and fantastical paradigm to grasp. However, the term, Brain-Computer Interface (BCI), was in fact, coined several decades ago, and was considered to be a technological revelation that emerged fairly ahead of its time. This revolutionary approach to interfacing breaks down conventional barriers that exclude the physically disabled demographic from using technology. While both invasive and non-invasive brain-computer interface technology exists today, the non-invasive method is largely favoured because of its portability, functionality and sans surgery approach. Over the years, many challenges have been encountered in this domain, particularly with regards to the unreliability of the electroencephalographic (EEG) signal, which manifests a whole range of consequential setbacks such as low information transfer rates and degraded BCI performance. While large strides have been made in this sector in recent years, challenges such as the variability and low signal-to-noise ratio of the EEG signal, still prevail. This paper outlines the progress made in the field of non-invasive BCI technology, and more specifically, the research efforts undertaken to improve the usability and performance of BCI systems. Results from these studies demonstrate that a hybrid BCI can indeed be effective in eliminating the unwanted phenomenon of illiteracy, and that SSVEP based BCIs have the potential to be the ideal BCI with their non-invasive approach, minimal training and high information transfer rates, in instances where external stimuli is used. The results also attested that the 4-8 is the optimal electrode configuration to obtain a better signal, and thus yield better BCI performance.

Author Keywords

Brain-Computer Interface (BCI); Electroencephalographic (EEG); Event-Related Synchronization (ERS); Event-Related De-synchronization (ERD); Steady State Visual Evoked Potential (SSVEP); Steady State Visual Evoked Response (SSVER); Amyotrophic Lateral Sclerosis (ALS); Magnetoencephalography (MEG); Positron Emission Tomography (PET); Functional Magnetic Resonance Imaging (fMRI); Event-Related Potential (ERP); Slow Cortical Potential (SCP); Information Transfer Rate (ITR); Signal to Noise Ratio (SNR); Inter Stimuli Interval (ISI); Fast Fourier Transform (FFT).

INTRODUCTION

A Brain-Computer Interface is a medium which allows direct communication between the brain and an electronic device. The underlying concept behind a BCI is to first capture the brain's electrical impulses under precise functioning and categorize those impulses so that output commands to a device can be established. However, BCIs should not be perceived as mind-reading devices, or as decryption systems of arbitrary, cognitive activities. Conversely, only well typified inferred brain activity patterns can be detected [9].

Several non-invasive techniques are now available to monitor brain function, namely electroencephalography (EEG), magnetoencephalography (MEG), Positron Emission Tomography (PET) and functional magnetic resonance imaging (fMRI) [10]. MEG, PET and fMRI have largely been dismissed as being too technically taxing and expensive, while EEG is identified as the only practical and inexpensive method for recording and processing brain signals. It is therefore, the optimal choice for BCI implementation [2].

Non-invasive BCIs typically use one of four types of electroencephalographic (EEG) activity for control: namely, steady state visual evoked potentials (SSVEPs), event-related de-synchronization and synchronization (ERD/ERS) and related rhythmic activity associated with imagined movements or other common mental tasks; P300s; or slow cortical potentials (SCPs) [1].

Typical BCI applications involve device control, letter or icon selection, or cursor manipulation. EEG-based brain computer interfaces (BCIs) can also provide a novel augmentative communication solution for completely paralyzed individuals, diagnosed with conditions such as ALS or other severe motor impairments. This is precisely why BCIs are mainly used today in this setting [10]. However, other applications for BCI technology also exist [2].

The following details an analysis and discussion on specific challenges encountered in the field of non-invasive BCIs and the approaches used to address them. The subsequent sections report the methodologies and findings of the examined BCI research studies, while also drawing conclusions on the progression of the field and identifying gaps in the knowledge base.

CHALLENGES

(i) Variability and Noise of EEG Signal

The EEG is an extremely complex signal, since it reflects the electrical fields produced by many trillions of individual synaptic connections in the cortex and in subcortical structures. EEG signals are bioelectrical potentials recorded from electrodes placed on the scalp. The measured potentials reflect the collective activity of large populations of cortical neurons located underneath the sensor position.
Thus, EEG has low spatial resolution and provides only a far-reaching and very noisy overview of brain activity.
This in turn, leads to further problems like low information transfer rates [9].

EEG is also known to be an extremely degraded signal, due to the complex anatomy and electrical characteristics of the cranium. Most importantly, it is an extremely variable signal. While the brain is capable of producing a given motor performance repeatedly with very slight variation, the brain activity underlying that output varies substantially from performance to performance. As a result, the EEG associated with a given output also exhibits variation. [10]

(ii) Electrode Placement

In BCI systems, the process of recording the brain signals, generated by the user is one of the principal parts of the system. With EEG as the tool, brain potentials can be recorded in the central-parietal scalp locations [1]. Because the non-invasive method is much more user-friendly and takes considerably less time to set-up, it is generally viewed as the more desired option for disabled individuals [2]. However, due to this lack of invasiveness, the recordings are done on the scalp, as opposed to, within the skull or within grey matter. As a consequence, the Signal to Noise Ratio (SNR) is low. So the challenge lies in deciding how many electrodes are to be used on the scalp and also determining their optimal locations for best results. The greater the number of electrodes used, the better the signal. However, there is a trade-off between accuracy and usability. Having a large number of electrodes in the EEG would generally take much longer to set up, when compared to having fewer electrodes. In many cases, the longer set-up time can dissuade the user from wanting to use the system.

(iii) Information Transfer Rates

Information Transfer Rate (ITR) is a measure used to calculate the amount of information (bits) that is transferred over time (per minute), also referred to as the bit rate. Current BCIs can be classified as being relatively low bandwidth devices, offering maximum information transfer rates of 5–25 bits/min at best [1]. At this rate, it may take several minutes to simply type a single word into a computer, thus making the user experience long and painful. It is highly probable that this time delay would cause users to get fatigued and agitated. The increase of ITRs would allow BCIs to offer all individuals useful ways of interacting with their environment [1].

(iv) Illiteracy

While BCI research efforts have succeeded in providing communication for some users, it is not yet clear whether BCIs could help all users [1]. As stated in [1], Brain-Computer Interface (BCI) systems do not function equally for all users, thus making universality a prime concern in BCI research.

A BCI user is considered illiterate if their accuracy classification is less than 70%. This occasionally occurs as each individual is different and therefore responds differently to the presented stimuli. So while the system may work smoothly for the majority of the demographic, there will be individuals who are unable to use this interface at all. This phenomenon of BCI-illiteracy needs to be eliminated to allow for a system that provides universality [1].

Improving BCI universality (that is, reducing illiteracy) should be a top priority. Improved training, subject instructions, and/or signal processing can make BCIs more universal, to some extent. [1]

(v) User Training

Another issue faced is the lengthy training time needed for BCI users to develop competence. BCIs that do not rely on external stimuli provide direct control over the environment, but these typical BCIs often require extensive training, from several hours to several months. BCIs based on evoked potentials may not need extensive training, but still do require a structured environment. [2]

[2] Showed that systems that use no external stimuli, and therefore allow for high user control, require more initial training than BCIs that do employ external stimuli. The challenge lies in creating a BCI that is natural to minimise the amount of needed training.

As stated in [5], previous BCI systems by Birbaumer at al (1999) included training sessions that lasted more than several months. Similar training session durations were also observed in the study by Pfurtscheller (2001) [5]. Although long periods may give the user in depth knowledge on how to use the system, the overall performance of the process is diminished due to the large amount of time dedicated to training.

APPROACHES

(i) Electrode Arrangement

In order to obtain the choicest signals from the BCI system, the number and placement of the electrodes must be taken into consideration. The best way to determine the most rewarding arrangement is by experimenting, using varying placements. The most extensive research on electrode placement was done by [5] where four electrode-placement combinations were tested. These used 4, 8, 16 and 32 electrode combinations respectively; this can be seen in Figure 1.

On the other hand, [1] used 5 bipolar electrodes placed at positions C3, Cz, C4, O1 and O2.

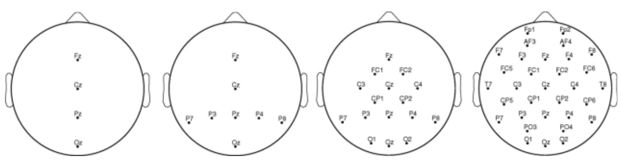

Figure 1: Electrode configurations used in the experiments: Configuration I (4 electrodes), Configuration II (8 electrodes), Configuration III (16 electrodes) and Configuration IV (32 electrodes) [5]

(ii) Signal Processing

[2] and [1] both, used steady-state visual evoked potentials (SSVEPs) recorded from the occipital scalp as inputs for their BCI systems. Systems which use SSVEPs as inputs have the advantage of focusing on EEG activity that occurs at a specific frequency. This characteristic simplifies the feature extraction methods, which means that users require little or no training [2].

EEG-based research in the ACT program also harnessed the steady-state visual-evoked response (SSVER) as an effective communication conduit for brain–computer interfaces [6]. Their second method of using multiple SSVERs for control required little or no training as the system capitalized on the naturally occurring responses [6].

SSVEPs can only be generated with stimuli frequencies higher than 6Hz. Using these recorded potentials, the amplitude spectrums can then be analysed to determine which stimuli caused the respective wave form. See Figure 2 for the evident peaks in the SSVEP recording at 7Hz, 14Hz and 21Hz, which can be concluded that a 7Hz stimuli has been evoked [2].

[5] used the control signal P300 as the potential to be detected in the human EEG. P300 is a positive deflection in the signals which arises 200-700ms after being presented to a stimulus, and is relatively easy to detect.

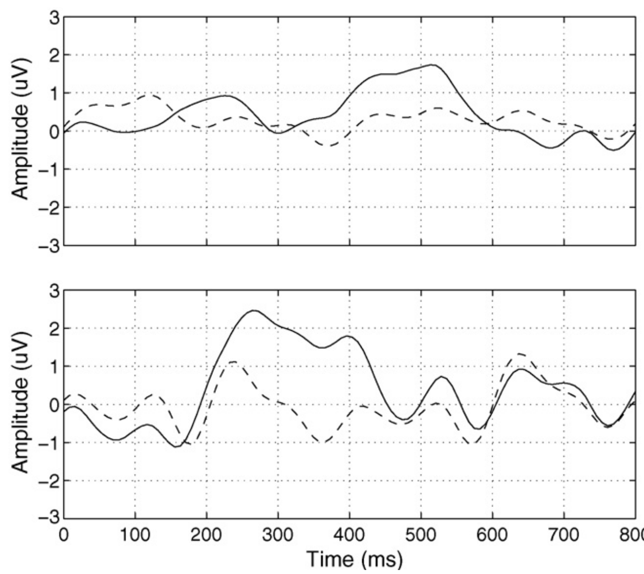

Figure 2: P300 waveforms of participants after a stimulus. (Top: Average waveforms for disabled participants. Bottom: Average waveforms for able-bodied participants) [5]

(iii) Stimuli

Research has been conducted to determine the impact of the difference between external and internal stimuli on user performance [1]. Internal stimuli cause Event-Related De-synchronization (ERD, which is achieved by the use of motor-imagery. The users produce potentials by imagining an explicit physical movement, which will, as a consequence, generate corresponding signals. Using internal stimuli gives a lot more freedom to the user, but on the other hand it also means that it is up to the user to create the correct imagery in order to generate a sufficient potential. The other form of stimuli, namely, external stimuli can be evoked on the user by using visual aids. These give rise to Steady State Visually Evoked Potentials (SSVEP) in the user. The potentials generated are to the response of visual cues such as flashing buttons or lights on a screen. The user has less control with this approach.

Secondly, if the stimuli are external, the visual layout of the interface can impact its interaction with the user. The presentation of the stimuli can increase or decrease the classification accuracy. Authors of [2] varied the frequencies of the flickering stimuli, the dimensions of the buttons on screen as well as the RGB values of the buttons to experiment which conditions resulted in the best classification accuracy, in order to determine whether a correlation exists in the instances between each stimuli and BCI system performance. Lastly, the duration of each external stimuli as well as the Inter Stimuli Interval (ISI) may also impact the overall performance of the system. [5] took this into consideration by selecting an appropriate ISI value and flashing duration that was long enough to generate a valid signal but was also within the desired session times.

Another possibility is a hybrid approach which includes both ERD and SSVEP stimuli being evoked simultaneously [1]. Hybrid BCIs could improve universality because a second approach might convey user intent if another approach cannot. Hybrid BCIs could also improve information throughput if subjects exhibit both types of activity [1].

(iv) Co-adaptive Training

One strategy to improve noisy EEG activity patterns is through the mutual optimization of pattern detector (machine learning) and pattern generator (human brain), better known as co-adaptive training [9]. The common practice is to firstly record EEG patterns from the user prior to BCI use and then train the pattern recognition algorithms. The trained models are then applied in real-time, and feedback on the detection quality is given to the user. Feedback training helps users in generating more distinct EEG patterns, which in turn, increases detection performance. These upgraded EEG patterns can then be used to retrain pattern recognition algorithms. The above steps are to be repeated until the desired performance level is reached. The required level of brain and machine co-adaptation depends considerably on the EEG signal types used to translate information [9].

METHODOLOGY AND FINDINGS

The research conducted in [1] was motivated by the goal to inspire more accurate BCI systems than conventional BCIs, especially for users who were unable to acquire at least 70% accuracy for effective communication (the accuracy classification standard to determine illiteracy). In order to achieve this, an original combination of tasks was introduced, typically used in two distinct BCI approaches, namely ERD and SSVEP. These approaches were used both, individually and collectively, in a ‘hybrid’ condition which effectively blended both tasks. Subjects visualised moving their left or right hand (ERD), fixed their attention on one of the two fluctuating visual stimuli, and then, concurrently carried out both tasks, all whilst EEG data was being recorded across the three conditions. [1]

Test participants were 14 healthy adults (6 women, 8 men; age range 17–31 years, mean 22.9), all of whom were undergraduate students. All subjects were free of any neurological or psychiatric disorders and were confirmed to have no usage history of medication known to adversely affect EEG recording. None had former experience with EEG recording or BCIs [1].

[1] also carried out an experiment with the aim of discovering the best form of stimulus creation in order to obtain the best BCI performance. Event Related De-synchronization (ERD) was tested where users were prompted to visualize one of the following two types of motor imagery: opening and closing of left hand or the opening and closing of the right hand. The second form of stimuli was the SSVEP. The participants were asked to concentrate on one of the two flashing LEDs which were oscillating at 8Hz or 13Hz. The final test was carried out to ascertain if a Hybrid of the two techniques listed above changed the results. Lastly, the participants were directed to perform both the ERD (visualize motor–imagery) while concentrating on the flashing LED (SSVEP) simultaneously.

Authors of [1] collected the results of ERD having a classification accuracy of 74.8%, SSVEP with 76.9% and Hybrid with 81.0%. The more significant finding was that users who were deemed BCI illiterate in either ERD or SSVEP (5 subjects in ERD, 5 subjects in SSVEP) were no longer illiterate in Hybrid (0 BCI illiterate subjects). Therefore, it was found that the use of the hybrid mechanism could indeed “educate” the otherwise illiterate participants, thus increasing BCI performance.

[2] presented a brain-computer interface (BCI) to help users enter phone numbers. The system was based on the SSVEP. Twelve buttons which lit up at different rates were displayed on a computer monitor. The buttons collectively represented a virtual telephone keypad, implying the ten digits 0–9, BACKSPACE, and ENTER. Users could input a phone number as a sequence of digits by gazing at these buttons. The frequency-coded SSVEP was used to determine which button the user desired. [2]

[2] conducted experiments using 13 healthy participants. The participants were comfortably seated in front of a computer screen which had a 3x4 matrix with digits, backspace and enter key. The rows and column of this matrix flashed randomly and the user had to count how many times their target cell had lit up as a selection

mechanism. The goal of the experiment was to successfully dial a given phone number using the BCI. The first task tested the ITR while the second task tested the button spacing theory. In an effort to increase reliability of the data collected by this experiment, the fast Fourier transform (FFT) was used. Four consecutive FFT had to be present for a positive detection to be confirmed. 8/13 participants were successful in dialing the phone number correctly, and the others were unable to do so. From the last task, it was found that it was in fact viable to have a high number of stimuli in a confined area without it affecting the performance or classification accuracy of the system [2]

Eight of the thirteen subjects succeeded in dialling the number correctly. The average transfer rate over all subjects was 27.15 bits/min. Consequently, after analysing the test results, the desirable features of this particular BCI system were identified as non-invasive signal recording, minimal required training, and high information transfer rate. [2]

[3] described a study which was designed to evaluate a previously formulated P300-based BCI [4]. Ten able-bodied (six female) and four disabled subjects (wheelchair-bound; three with complete paraplegia, one incomplete paraplegia; two female) from the university community participated in the experiment.

The evaluation was conducted by employing a bootstrapping approach, which demonstrated that an off line version of the system could communicate at the rate of 7.8 characters a minute and also attain an 80% accuracy. In addition to the offline assessment, the real-time performance of the BCI system was also measured. The results indicated that the P300-based BCI was both practical and viable. The study also confirmed the earlier report by Farwell and Donchin [4], that a BCI can indeed be constructed using the P300, which allows an individual to manipulate a virtual keyboard without the need of any skeletal muscle activation [3].

It was also observed that the BCI described in this particular study outperformed Farwell and Donchin's BCI [4], as far as communication rates were concerned. Under the conditions of the present study, the communication speed at which the system allowed communication at the 80% level of accuracy was 7.8 characters/minute. The speed decreased to 4.8 characters/minute at the 90% accuracy level. This demonstrated a substantial improvement when compared to the rates reported by Farwell and Donchin [4]. One significant difference between the BCI used in this study and the previous BCI was that the discriminant analysis in this study was applied to the 36 individual cells rather than to the rows and columns. It was observed that it was this tactic which most likely caused the detection to execute with greater sensitivity. However this was not confirmed [3].

[5] conducted extensive research on electrode placement and also explored the differences between healthy and disabled participants as a response to their BCI systems. Four configurations of electrode placements of 4, 8, 16 and 32 electrodes were used. 4 disabled and 5 able-bodied subjects took part in the experiment. The participants were presented 6 images; TV, lamp, radio, door, window and telephone, in order to control various electronics in a house. These images flashed randomly in front of them and the participants had to keep track of how many times their target image had flashed. It was found that when using an 8-electrode configuration, 6/8 participants got an average of 100% classification accuracy. The highest accuracy was recorded when using either the 4 or 8-electrode configuration. Increasing the number of electrodes further from 8 did not significantly improve accuracy in any form. However, it was noted that using more than 8-electrodes in some cases, actually caused a lower amplitude signal to be generated. There was no distinct difference in performance between the disabled and able-bodied users. However, the rise in classification accuracy was found to be slower in disabled subject when compared to the healthy subjects [5]. [5] also obtained the highest bit rate of all the other experiments at 25bits/min.

The Air Force Research Laboratory also implemented and evaluated two brain–computer interfaces (BCI's) [6]. Their systems translated the steady-state visual evoked response into a control signal in order to operate a computer program or physical device. In one approach, operators were expected to self-regulate the brain response while the other approach used multiple evoked responses.

Two virtual buttons (2.9 by 3.8 cm) were displayed on the left and right sides of a monitor (separated by 10.3 cm) and regulated at 23.42 and 17.56 Hz, respectively. The buttons were viewed at a distance of 71 cm, resulting in visual angles of 3.0° vertically and 2.3° horizontally. This BCI system was experimentally assessed using eight participants. Their task was to select the virtual button indicated by a yellow command box. Participants performed 200 trials each, with no training trials. The participants averaged 92% correct selections (range: 83–99) with an average selection time of 2.1 s [6].

[7] involved an offline study of the effect of motor imagery on EEG and an online study that used pattern classifiers incorporating parameter uncertainty and temporal information to discriminate between different cognitive tasks in real-time. In order to keep the system as simplistic as possible, the initial prototype only made use of three electrodes, a single isolation amplifier and a 266-MHz PC. The electrodes were placed 3 cm behind C3 and C4 while a reference electrode was positioned over the right mastoid. Subjects moved a cursor on a computer screen and attempted to hit targets appearing at the top or bottom of the

screen. Cursor movements were driven by two different types of cognitive tasks:
1) motor imagery versus a baseline task and
2) motor imagery versus a math task.
For the motor imagery tasks, subjects were asked to visualise opening and closing their hand (right or left according to handedness), and for the maths tasks, subjects were asked to successively subtract seven from a large number. "Stationary cursor trials" were also carried out, in which the cursor would not move. In this particular trial instance, cursor movements were generated by extracting autoregressive (AR) features from the EEG and classifying them using a Bayesian logistic regression model.

Results were reported from online experiments by analysing the EEG data on a segment-by-segment basis. In the stationary cursor trials, the imagery versus maths pairing was more easily differentiated than the imagery versus baseline pairing, and this difference was notable in four of seven subjects. In the moving cursor trials, however, the two different task pairings were equally well differentiated. An analysis of the spectra associated with each cognitive task showed that, for most subjects, the majority of differential activity is in the µ-band (8–13 Hz) while some subjects also showed differences in the beta (14–20 Hz) band and, for the maths tasks, also in the theta (4–7 Hz) band [7].

Overall, in the moving cursor trials, four out of seven subjects achieved at least 75% accuracy. In this instance, accuracy is defined as the percentage of correctly classified data segments. The average accuracy over all seven subjects was 61% which, it was noted, could be increased to 87% with the use of a reject option. These figures corresponded to bit rates of 0.02, without a reject option, and 0.12 with a reject option; a six-fold increase in communication rate. This upper bit rate corresponded to communicating two to three letters of the English language per minute, which is quite fast as far as BCI information transfer rates are concerned. A further benefit of using a reject option was identified as the observation that sections of EEG containing irrelevant cognitive components (e.g., during lapses of concentration) do not result in spurious cursor movement. This greatly enhances the robustness of the system. [7]

SUMMARY

Non-invasive Brain-Computer Interfaces have evolved considerably over the past few decades, in tandem with the rapid advances in science and technology. Insights into the EEG signal and its limitations have spurred research to address the consequential problems with a broad range of results. The successful use of the hybrid BCI system in minimising illiteracy must be explored further to determine the underlying cause of the improved performance [1]. The usage of SSVEP based BCIs should also be substantiated further to determine whether the research conducted which described characteristics of non-invasiveness, minimal training and high information transfer rates, was merely an anomaly or in fact, a certainty [2]. Also, since the research done on optimal electrode configuration was quite conclusive and thorough, it would be wise to use the 4-8 electrode configurations for future BCI systems. Additionally, stimuli variation, optimal electrode arrangement, signal processing techniques and co-adaptive training should be continually put into practice, to further reduce the adverse effects of the hindrances encountered in the field of BCIs. While there is still plenty that needs to be accomplished before BCIs are ready to be deployed to the general public, specifically in terms of improving usability and performance, the progress that has been made in this field in such a short span of time is noteworthy. But, in order to ensure that progress continues to climb, complacency must be avoided and the challenges in BCIs must be faced squarely. Issues like the variability of the EEG signal and its consequences, long training times, illiteracy and low information transfer rates which degrade BCI performance must be frankly identified as the roadblocks which obstruct further advancement, and research must continue, to discover innovative and cost-effective solutions to these problems.

FUTURE WORK

Further work should explore precisely why the hybrid condition yielded better accuracy, evaluate online performance, and also address numerous other options for various types of hybrid BCI systems [1].

The work described in [1] only explored the possibility that a hybrid BCI could improve accuracy, and thereby universality. However, information transfer rate (ITR) depends on the number of selections per minute (S) and the number of selections available (N), as well as accuracy (P). Other hybrid BCI paradigms could instead aim to increase S or N instead of P.

In the future, experiments should be conducted with completely locked-in participants to evaluate the real usability of the system. [2] hopes to use CTR monitors in the future to allow for a higher refresh rate, which would, in turn, greatly impact the performance of the BCI systems.

While the observed improvement in the BCI in [3], when compared to the older P300 based BCI [4] was identified as being the probable effect of the adopted strategy of applying the discriminant analysis to the 36 individual cells rather than to the rows and columns, the authors stated that all the underlying factors would need to be further investigated, before any concrete conclusions could be reached. [3]

Despite the success demonstrated with the self-regulation based BCI, substantial training is required. For this reason, the ACT program aims to focus its future BCI efforts on approaches that use naturally occurring SSVER's. The next step with this BCI will be to compare its performance to that of a standard computer mouse using a Fitts' Law paradigm in order to evaluate the speed and accuracy of the two controllers [6].

There is also a need to persevere with methods involving little or no biofeedback training and also to focus on other ways of improving classification accuracy [7]. Additionally, the concept of training subjects using a biofeedback approach also warrants some exploration. This involves the interaction of two adaptive controllers; the user and the computer.

Also, other paradigms of visual feedback such as games should be examined more thoroughly to determine whether better visualization of the signal could optimise and improve the effectiveness of training, thus reducing illiteracy [8].

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