Increasing Performance in Brain Computer Interfacing

Hasini Ratnasekera Faculty of Engineering Software Engineering grat012@aucklanduni.ac.nz 1184104

ABSTRACT

Brain-Computer Interfacing is an innovative system to aid disabled individuals to interact with the computer interfaces. This form of interaction is very useful to the disabled demographic since the motor functions required for ordinary computer interfaces are impractical. Many challenges are present in the current systems with regards to the large number of illiteracy present in participants when using Brain-Computer Interfaces, understanding the optimal placement of electrodes when recording signals, the low information transfer rates currently present as well as the extensive training demanded by the present systems.

This paper outlines the work done by [1-6] as an attempt to decrease the impact of the current challenges.

Author Keywords

Brain-Computer Interaction (BCI); Electroencephalographic (EEG); Event-Related Desynchronization (ERD); Steady State Visual Evoked Potential (SSVEP); Visual Evoked Potential (VEP); Amyotrophic Lateral Sclerosis (ALS); Locked-In Syndrome (LIS); Event-Related Potentials (ERP); Information Transfer Rate (ITR); Bayesian Linear Discriminant Analysis (BLDA); Fisher's Linear Discriminant Analysis (FLDA); Inter-Stimulus Interval (ISI); Signal to Noise Ratio (SNR)

INTRODUCTION

There are various forms of technology in abundance for healthy ordinary users available at present day that has the ability to perform very complex tasks. But the interaction between disabled individuals and computers are still slow, unpleasant or in some cases nonexistent. The requirement for assistive technologies for such individuals is high and is a basic need of communication for disabled individuals. Brain Computer Interfacing (BCI) introduces a new paradigm of interaction where a computer interface can be controlled without the use of peripheral nerves or muscles [2] [4] [5]. This allows patients suffering from minor disabilities of weak limb movements, to more severe cases of Amyotrophic Lateral Sclerosis (ALS) or Locked-In Syndrome (LIS) [1] to control a computer interface by generating brain signals.

BCI is a newly emerging area of research developed over the past few decades which continuously grows and improves over time with new findings. Although the BCI system has been established as a functional interaction mechanism, there exists much room for improvement to allow BCI to become a usable tool for disabled individuals. BCI can be applicable to both healthy and disabled users in various applications. The signal collection can be done in one of two forms; invasive or noninvasive. The signal type collected as well as the type of stimuli generating this brain signal can also be varied across experiments.

This paper will focus on non-invasive BCI systems using Electroencephalographic (EEG) to detect the potentials generated by disabled user's brain signals. The various problems faced in present BCI systems with regards to performance will be discussed and the approaches that can be taken to minimize these issues will be outlined.

CHALLENGES

The following issues of BCI limit the systems' usability and performance. Some past BCI research will be discussed to show the challenges which arise when carrying out this new Interface.

(i) BCI Illiteracy

As stated in [1] and [6] a BCI user is considered illiterate if the accuracy classification for this user is less than 70%. This occasionally occurs as each individual is different and reacts differently to the presented stimuli. So while the system may work very well 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 removed to allow for a system that provides universality [6].

(ii) Electrode placement

Recording or picking up the signals generated by the user of BCI is one of the main processes of the system. Using EEG as the tool, it allows for brain potentials to be recorded in the central-parietal scalp locations [1]. Because the noninvasive method is more user-friendly and has a faster set-up, it generally will be the more desired option for disabled individuals [2]. Having said this, because the recordings are done on the scalp, the Signal to Noise Ratio (SNR) is low. So the challenge is to firstly decide how many electrodes to be used on the scalp and secondly on where they should be placed for best results. It can be assumed that the greater the number of electrodes used will provide a better signal. But there exists the tradeoff between accuracy and usability. Having a large number of electrodes

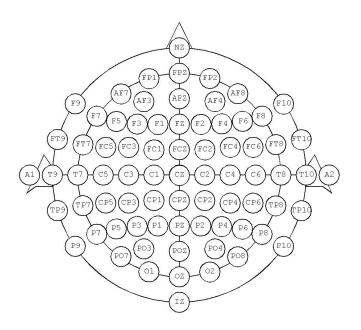


Figure 1: Map of all possible locations for the placement of EEG electrodes on a human scalp

in the EEG would generally take much longer set-up duration than fewer electrodes. This can in many cases decrease the tendency of a disabled individual from using 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. Most present BCI systems have a very low bit rate, which means that the interaction between the user and the interface is very slow, causing the experience to be very time consuming. This may cause users to get fatigue and become frustrated [5]. [2] has outlined that the ITR of past system range between 5-25bits/min, which consequently would take several minutes to input a word.

(iv) Training

Training is a process that must be present in all BCI systems, but the degree and duration of this may greatly vary. The problem with currently available BCI's is that they require a long duration of training in order to use the system successfully. This decreases the usability immensely due to the learning curve of using a BCI system is evidently large. As stated in [3], previous BCI by Birbaumer at al (1999) had training sessions that spanned over several months. Similar length of time was also taken by Pfurtscheller (2001) [3]. Although this may give the user a thorough training on how to use the system, the overall performance of the process is decreased due to the mass amount of time dedicated to the training. [2] Showed that

systems that allow for high user control, such as those using no external stimuli, require more initial training than BCIs that use external stimuli. The challenge is to create a BCI that is natural which would require minimal training.

APPROACHES

The approaches taken by [1-6] are described below as an attempt to minimize the challenges faced by BCI.

Electrode arrangement

To obtain the best possible signals from the BCI system, the quantity and placement of the electrodes must be taken into account. The best way to determine the most rewarding configuration is by experimenting using varying placements. In [1], a 16 electrode cap (Electro-cap International) was used with locations Fp1, Fp2, F3, Fz, F4, T7, T8, C3, Cz, C4, Cp3, Cp4, P3, Pz, P4 and Oz. On the other hand, [6] used 5 bipolar electrodes placed at positions C3, Cz, C4, O1 and O2. The exact locations of these electrode placements can be seen on Figure 1.

The most extensive research on electrode placement was done by [3] where four electrode-placement combinations were tested. These used 4, 8, 16 and 32 electrode combinations respectively; this can be seen in Figure 2.

Stimuli

The majority of the system's success relies on the manner that the stimuli are presented to the user. The stimuli can be broken down into three areas. Firstly the type of signal generated by the stimuli, secondly the visual presentation of the stimuli, and finally the duration of the stimuli.

Stimuli could be generated by the user, evoked on the user or a combination of both. [6] researched on how the difference of external and internal stimuli impacted the performance of a user. Internal stimuli cause Event-Related Desynchronization (ERD). ERD is carried out by the use of motor-imagery. The users generate potentials by imagining a specific physical movement, which will as a consequence generate corresponding signals. The stimuli itself are usergenerated and therefore it is an asynchronous approach to BCI. It gives a lot more freedom to the user, but on the other hand it means that it is upon the user to create the correct imagery to generate a sufficient potential. The other form of stimuli can be evoked on the user by using visual aids. These evoke 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 in this process. [6] also proposed a hybrid approach which includes both ERD and SSVEP stimuli being evoked simultaneously.

Secondly, f 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. The authors of [5] varied the frequencies of the flashing buttons, the dimensions of the buttons on screen as well as the RGB values of the buttons to experiment which conditions created the best classification accuracy. Authors of [2] also took a similar approach to see if a correlation exists in the distances between each stimuli and the system performance.

Lastly, the duration of each external stimuli as well as the Interstimuli Interval (ISI) may also impact the overall performance of the system. Both [1] and [3] 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.

Signal Processing

Different authors decided upon specific signal types to be recorded and analyzed. The various signal processing approaches by [1] [2] [3] and [6] are described here.

[3] 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. This is relatively easy to detect.

[2] and [6] on the other hand, both used SSVEP or Visually Evoked Potentials (VEP). Transient VEP are generated in response to stimuli with frequencies less than 2Hz. SSVEP can only be generated with stimuli frequencies higher that 6Hz. Using these recorded potentials, the amplitude spectrums can be analyzed to gather which stimuli caused this wave form. The harmonics of the stimuli frequency can be seen within the spectrum to easily determine which stimuli resulted in the generation of the waveform. See figure 3 for the evident peaks in the SSVEP recording at 7Hz, 14Hz and 21Hz, which can be concluded that a 7Hz stimuli has evoked [2].

Signal processing can be done online or offline. In the case of online-BCI, the results are calculated online as the recordings are taken. In the case of offline processing, it reflects the expected classification coefficients derived from other expanded and external feature spaces [1]. The authors of [1] tested which approach, online or offline generated the best performing BCI.

The BCI systems need to be reliable. When a BCI is created, it needs to be ensured that the results generated from this system will be consistent and long lasting. [1] did extensive research and testing over a time period of 50 weeks to collect data to test the hypothesis of whether a BCI system will provide approximately the same accuracy classifications as well as the latency.

METHODOLOGY AND FINDINGS

[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 this interface. The first task tested the ITR while the second task tested the button spacing theory. The fast Fourier transform (FFT) was used to increase reliability of the data collected by this experiment. 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 other could not. From the last task they 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. As the button spacing between the stimuli was decreased to have minimal space separations, the accuracy was not impacted [1]. Therefore the ability to have many stimuli in a small area can increase the ITR as a consequence [1].

Likewise [5] also conducted experiments which test the appearance of stimuli and its impact on the performance. A web browser interface was presented to the participants with 4 flashing rectangular buttons on the peripherals of the screen. This served as a navigation system to move within a web browser. The buttons flashed at differing frequencies and the SSVEP recording from the EEG were taken. The flashing frequencies of the buttons were ranged between 50ms – 85ms. The height of the button was increased from 10-100pixels. Finally the RGB values were ranged between 160-180RGB.

They found that the highest amplitude potentials were evoked with the following conditions: 65ms frequency flash, a large 100pixel button size and a moderately high RGB of 160-180. Therefore moderate frequencies with large stimuli that are relatively bright generate the best results [5].

[4] attempted to overcome the ITR by conveying the users intent prior to the event is supposed to take place. The authors of [4] created a intelligent system that is in the form of a robotic wheel chair. The robotic wheelchair is capable of detecting corridors and doorways on its own. Therefore to decrease the ITR of BCI system, they have generated the idea of "convey the user's intent". The user will issue the command prior to the doorway, and therefore the signal will be detected prior to reaching the doorway, which will in turn increase the system's performance.

[6] carried out an experiment which hoped to find the best form of stimulus creation in order to obtain the best performance. ERD was tested where users were prompted to visualize one of the following 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 directed to concentrate on one of the two flashing LEDs which were oscillating at 8Hz or 13Hz. The final test was to see if a Hybrid of the two techniques above changed the results. So finally the participants had to perform both the ERD (visualize motor–imagery) while concentrating on the flashing LED (SSVEP) simultaneously.

Authors of [6] collected the results of ERD having a classification accuracy of 74.8%, SSVEP with 76.9% and Hybrid with 81.0%. The more important finding was that users who were tagged 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 the use of hybrid mechanism can mask the other wise illiterate participants, and as a result increasing the performance of the system.

[3] conducted the extensive work on electrode placement as well as the differences between healthy and disabled participants as a response to their BCI system. They used four configurations of electrode placement of 4, 8, 16 and 32 electrodes. The experiment consisted of 4 disabled and 5 able-bodied subjects. Most of these disabled subjects were also had LIS. The participants were presented 6 images; TV, lamp, radio, door, window and telephone, in order to control varicose electronics in a house. These images flashes randomly and the participants had to keep count of how many times their target image had flashed.

They found that using 8-electrode configuration, 6/8 participants got an average of 100% classification accuracy. The best accuracy was recorded using either the 4 or 8-electrode configuration. Increasing the number of electrode further from 8 did not show any significant improvements to the results. However having more than 8-electrodes in some cases, caused a lower amplitude signal to be generated. There was no evident difference in performance between the disabled and able-bodied users. However the rise in classification accuracy was slow in disabled subject when compared to the healthy subjects over the course of the sessions [3]. [3] also obtained the highest bit rate of all other experiments of 25bits/min.

Finally [1] conducted experiments to allow Amyotrophic Lateral Sclerosis (ALS) to spell using the BCI system. 8 ALS participants undertook this experiment to carryout spelling tasks. Phase I consisted of "copy-spelling" which prompted the participant to spell a given word using the BCI matrix. Phase II allowed for "free-spelling" which enabled the participants to spell any word. They conducted this experiment repeatedly over 40 weeks to check the results.

They found that the classification accuracies and the latency of the signal did not change over the weeks of testing and it can therefore be classifies as being reliable. During the signal processing phase, they found that the offline method increased the performance by 20% as compared to the online method. Subjects that were classed BCI-illiterate in online BCI were found to be literate in the offline processing.

FUTURE WORK

In the future, experiments should carried out on completely locked-in participants to test the real usability of the system. [2] hopes to use CTR monitors in the future to allow for higher refresh rate, which would greatly impact the performance of the BCI systems.

SUMMARY

From the various experimentation of the authors of [1-6], a vast number of approaches have been taken to improve the challenge of limited performance in Brain Computer Interfaces. It can be concluded that using a hybrid mechanism of a combination of ERD with SSVEP stimuli as well as offline processing can minimize the presence of BCI-illiteracy. Using an 8-electrode EEG system has also been proved to be the most optimal electrode configuration. The application systems can be also optimized by having several stimuli on screen which are large in size and bright in color. Information Transfer Rate and as a result the performance of a system can be increased by following the above findings.

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LIST OF FIGURES

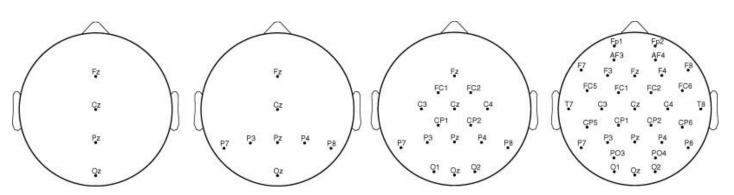


Figure 2: Electrode configurations used in the experiments: Configuration I (4 electrodes), configuration II (8 electrodes). Configuration III (16 electrodes) and configuration IV (32 electrodes) [3]

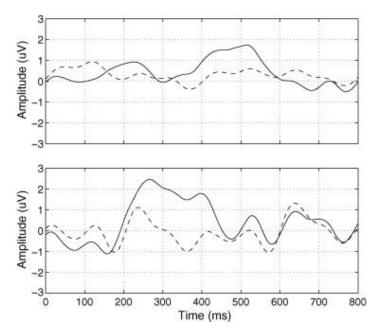


Figure 3: P300 waveforms of subjects after a stimulus. Top: average waveform for disabled subjects. Bottom: average waveforms for able-bodied subjects.