A Review of Asynchronous Electroencephalogram-based Brain Computer Interface Systems

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Abstract. Various researches on brain computer interfaces have been conducted for physical impaired to control an electronic assistive device using only their brainwaves or scientifically known as electroencephalogram (EEG). The problem of current EEG-based brain computer interface (BCI) system is its performance in accuracy and time response. There are two types of BCI; synchronous and asynchronous. Synchronous BCI is a cue based system which is restricted to a predefined time frame whereas an asynchronous BCI is a self paced system which operates independently of a cue stimulus. The main objective of this review study is to conduct a literature review on the effect of asynchronous design to the accuracy and time response of BCI systems. From the scope of EEG signal processing, research papers and conference proceedings had been collected and reviewed from abstract to conclusion. Results from five significant researches has been compiled and compared. The findings obtained in this study will be significant to researchers and engineers pursuing in EEG-based BCI system in biomedical and health science industry.

Keywords: Electroencephalogram (EEG), Brain Computer Interface (BCI), Asynchronous, Non Control (NC), Intentional Control (IC)

1. Introduction

Electroencephalogram (EEG), which is also known as "*Brainwaves*" is a recording of brain's electric potentials from electrode placed on the scalp. The electric potentials can be characterized into two; spontaneous and evoked potentials. Spontaneous potentials can be seen during mental task such as motor imagery, resulting in event-related desyncronization and synchronization (ERD/ERS). Conversely, evoked potentials or steady states visual evoked potentials can be seen after an external stimuli applied where the brainwaves frequency synchronizes with the frequency of the applied stimuli [8].

Brain Computer Interface (BCI) is a system which connects the brain to an external device. The external device can be as simple as a feedback monitor or as complex as a prosthetic limb. Electrical potentials from the brain shall be measured by the electrodes placed on the scalp. As the signal is very weak, it shall be amplified and input to the computer. The computer shall then extract the features and classified them to predefined set of instructions. Then an external device or a feedback monitor responded to the given instruction. The earlier studies on EEG-based assitive device is to move a cursor and a switching device. It is already being implemented in clinical application for the patient to communicate with others [7].

Recent studies show a variety system design which implements either synchronous or asynchronous BCI system. In synchronous BCI, every features of the signal is extracted and processed sequentially. Only after

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the first instruction is completed, then only the system allows another set of feature to be processed. The system is also known as a cue-based type [10].

However, an asynchronous BCI system is independent of the cue-based manner. The features extracted and processed are not necessarily followed by an instruction. The system can accept and process the features one after another without waiting for the first instruction to be completed. It is also known as a self paced type [1]-[5]. This paper focus on asynchronous design as it is an ideal for a BCI to work independently of a cue stimulus.

The problem faced by current BCI system is its accuracy and time response. Various studies conducted to improve the parameter measures of the system such as accuracy and time response. Current EEG-based BCI system has accuracy rate of 75-90% and time response of 4-12sec [10]. It needs major improvement in accuracy and time response as it involves the safety of the user.

The main objective of this paper is to review relevant researches on asynchronous EEG-based BCI system so that the performance of their system design can be analyzed. It is significant for researchers or engineers pursuing in EEG-based BCI system in order to improve the accuracy and time response. Next section will explain further on the methods used in reviewing related researches.

2. Methodology

The scope of work covers the topic of asynchronous EEG-based BCI system designs. First a framework is required in order to conduct a structured literature review. Independent variables (IVs) and dependent variables (DV) involves has been identified and illustrated in Figure 1[6], [9].
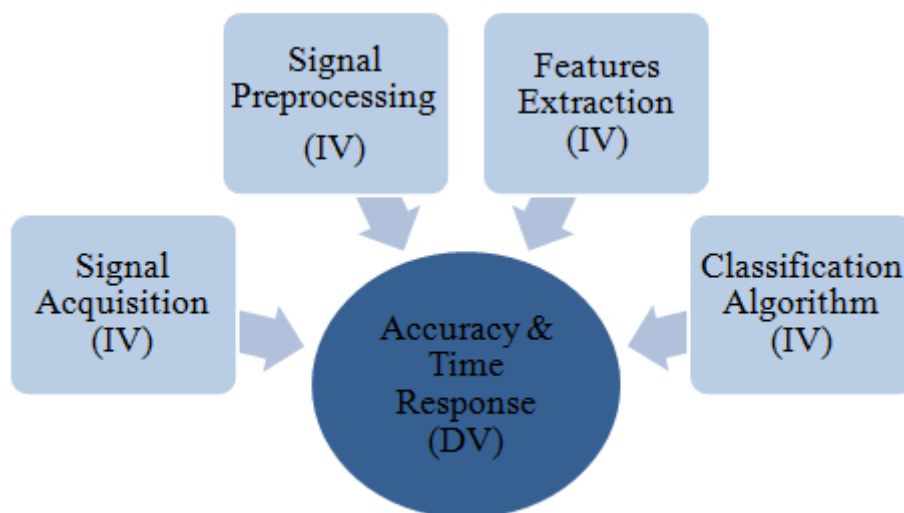

Figure 1 Framework of review paper

This review paper will analyze the effects of selected independent variables to a BCI system performance. Signal acquisition is obtained from the sensors or electrodes placed on the scalp. Various measures need to be considered before and during the signal acquisition session in order to obtain correct data. One of the measures to consider is the location of the electrodes. For BCI system design using motor imagery, usually it is enough to place electrodes at the sensorimotor cortex area which shows significant brain activity during motor imagery [2]-[4]. Normally, the larger amount of electrodes is better but that is not necessary as long as the system knows which signal to look for.

As the electrical activity measured from the scalp is very small, the signal needs to be amplified. When a signal is amplified, the noise which corrupts the signal during recording will also be amplified. To compromise with the existence of noise in the signal, filtering or signal preprocessing is required. There are various methods to filter the noise and extract the features but it will not be covered in this paper. This review paper will further compare and discuss on the design of classifier algorithms only.

Figure 2 shows the methodology flowchart of this review paper. Starting from the macro-scope under EEG signal processing, research papers and conference proceedings for the past 3 years had been collected

and briefly reviewed from abstract to conclusion. A selection was made to collect and divide relevant researches with those irrelevant.

After the selection, detail review was conducted to be analyzed. The results of the findings will be explained and discussed later in the next section. The findings compared the results of five significant researches related to the topic. Comparison of parameter measures are based on the variables and framework of this study. Finally, conclusion and future recommendations are made based on the findings.
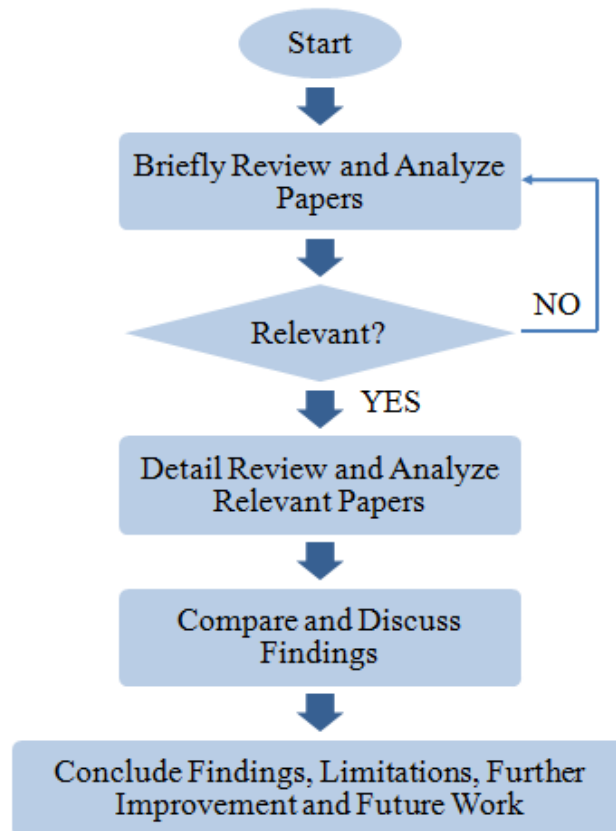

Figure 2 Flowchart of review activities

3. Results & Discussion

This section is divided into two parts; results and discussions. Five different and significant researches have been chosen for this review paper. The summary and comparisons are listed in Table 1 below.

Firstly, Case A introduces a novel method to control the duration of Non-Control (NC) and Intentional Control (IC) states (Motor Imagery (MI) for left, right hand, foot and etc.) using Cumulative Incremental Control (CIC) strategy. This method calculates the duration of the Event-Related Desynchronization/Event-Related Synchronization (ERD/ERS) states which is different with common system that only detects the existance of ERD/ERS states. The phenomena is called as task related sustained desynchronization/synchronization (TRSD/TRSS) or steady state event related (de)synchronization.

One of Case A findings is that the TRSD and TRSS are significantly enhanced when simultaneously performed left hand and foot, or right hand and foot movement. From this observation, it is possible to have more IC states instead of normal individual left, right hand and foot motor imagery. Problem faced is probably the accuracy rate decrease to 76% for one sec of MI time from 91% for four sec of MI time. More training is required in order to control the speed and steering angle of the virtual car due to longer the duration of MI, larger the steering angle. The steering angle is very sensitive to error classification.

Case B objective is to introduce novel reject options to discriminate between NC and IC states. They introduced three reject options and applied it to four classifiers as listed in Table 1. One of their recommendations is to incorporate ambiguity rejection with outlier rejection to improve the accuracy rate.

This is because Threshold of Reliability Functions (TFR) together with Linear Discriminant Analysis (LDA) has the highest accuracy even though it has the lowest rejection capability.

Case C introduces a hybrid BCI where they combine Steady-State Visual Evoked Potential (SSVEP)-based BCI and ERS-based BCI to control a hand orthosis. The SSVEP is used to discriminate the NC and IC states, which they called it as "Brain Switch" and ERS to classify four classes of MI. This research provides new idea in combining both SSVEP and motor imagery in one system. It can be observed that the limitation of this design is its reliance on external stimuli (flickering light). An ideal BCI system should also use a brain-based switch as introduced by [2].

Case D introduces additional algorithm to improve the accuracy of a normal BCI. By using anti-biasing and multiple thresholding, the True Positive Rate (TPr) and False Positive Rate (FPr) improved significantly. The significant result from this research is that anti-biasing helps to successfully improve the detection the NC states.

Finally, Case E objective is to maximize the bit rate and accuracy of a SSVEP-BCI system. According to their research, SSVEP-BCI system has gradually becoming unpopular in latest BCI system due to its restriction on external stimuli. From the results obtained, the lowest Error Rate (ERR) achieved using 4 sec data window length. By comparing results from Case A and Case E, the data window length is nearly similar but the accuracy is better in Case A. Even though Case E objective is to improve the bit rate using SSVEP, Case A managed to get better result using motor imagery with no external flickering stimuli.

Table 1 Comparisons between five asynchronous EEG-based BCI system.

Reviewed Papers	NC and IC States Classifier	Motor Imagery-IC States Classifier	Results
Case A [1]	Statistical Rejection Criteria	Common Spatial Frequency Patterns (CSFP)	Speed and steering angle controlled by type and duration MI
		Cumulative Incremental Control Strategy (CIC)	Best accuracy obtained 76% for 1 sec MI time and 91% for 4 sec MI time
Case B [2]	Threshold of Reliability Functions (TFR)	Support Vector Machine (SVM)	RC has the highest accuracy of fixed 10% False Acceptance Rate (FAR)
	Specialized Classifier (SC)	Radial Basis Function Network (RBFN)	
		Fuzzy Inference System (FIS)	FIS, RBFN and SVM provided best rejection
	Rejection Class (RC)	Liner Discriminant Analysis (LDA)	
Case C [3]	SSVEP- Power Density Spectrum (PDS)	Liner Discriminant Analysis (LDA)	NC states False Positive Rate (FPr) reduced by 50%
Case D [4]	Particle Swarm Optimization (PSO)	Common Spatial Pattern (CSP)	TPr of 76.1% (6% increment) and FPr 20.2% (11% decrement) compared to normal BCI system without anti-biasing and multiple thresholding.
		Eigenvector Filtration	
	Anti-biasing	Savitzki-Golay Smoothing	
		Multiple Thresholding	
Case E [5]	SSVEP	Common Spatial Pattern (CSP)	Error rate (ERR) decrease significantly as the data window length increases.

4. Conclusion

From the findings, most researches focused on only accuracy or time response separately. The future recommendation is to optimize the performance of both accuracy and time response because both are equally important in a BCI system. The more complex its classifier, the more time required to process the signal. Another problem faced in asynchronous BCI system design is to accurately classify the NC and IC states. An alternative solution to improve accuracy is by combining suitable classifiers into one system.

Asynchronous BCI has only been researched recently compared to synchronous BCI but conversely a lot more can be explored to improve its performance. It is not possible to compare the results obtained from an asynhcronous BCI with a synhcronous BCI in terms of accuracy and time response. It is recommended to use appropriate analysis for measuring the performance of asynchronous BCI. For example, an asynchronous BCI uses the False Positive/True Negative Rate to measure the system accuracy but synchronous BCI normaly uses overall accuracy.

It can be observed that the accuracy of an offline system without feedback is always better than an online system with feedback. Even with the same classifier, the results will not be the same. So, the robustness of the classifier need to be taken into consideration in designing an online BCI system as it continously process the signal. Another solution for robustness is by using an adaptive classifier. Futher studies should be made on other factors besides classifier which affects the accuracy and time response of an asynchronous EEG-based BCI system.

5. Acknowledgements

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