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Research Article

Engineering

THE ANALYSIS OF MOTOR IMAGERY AND SSVEPS FOR THE BCI APPLICATION

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Abstract

Many studies have shown that the electrical and magnetic fields generated during brain activities can produce certain signals. Some of these signals can be captured using electroencephalography, a detection tool involving mobile brainwave sensors whose use has matured and become affordable. The brain-computer interface (BCI) provides an alternative form of communication between the human and a system (computer or actuator) without any physical contact between them. There are many ways to evoke brain signals for translation into computer tasks, but the most popular are motor imagery and steady-state visual evoked potentials (SSVEPs). In this research, an offline analysis of motor imagery and SSVEPs based on BCI experiments that use electroencephalography (EEG) is reported. The results show that SSVEPs are more accurate and convenient than motor imagery, with errors of 15 percent and 35 percent, respectively.

Keywords: brain-computer interface, brain signal, electroencephalogram, motor imagery, steady-state visual evoked potential.

摘要：许多研究表明，大脑活动期间产生的电场和磁场可以产生某些信号。 其中一些信号可以使用脑电图捕获，这是一种涉及移动脑波传感器的检测工具，其使用已经成熟并且价格合理。 脑 - 计算机接口（BCI）提供了人与系统（计算机或致动器）之间的另一种通信形式，它们之间没有任何物理接触。 有许多方法可以唤起大脑信号转化为计算机任务，但最常见的是运动想象和稳态视觉诱发电位（SSVEP）。 在这项研究中，报道了基于使用脑电图（EEG）的 BCI 实验的运动想象和 SSVEP 的离线分析。 结果表明，SSVEPs 比运动图像更准确，更方便，误差分别为 15％和 35％。

关键词: 脑 - 机接口，脑信号，脑电图，运动想象，稳态视觉诱发电位。

I. INTRODUCTION

The brain is a vital internal organ that is located within the skull. All human activities are controlled via some parts of the brain. Nerve signals are transmitted from the brain to motor muscles all the time as are impulses toward other body parts, facilitating engagement in some activities.

From the neuroscience point of view, the peripheral nervous system is divided into 2: the autonomic nervous system (ANS) and the somatic nervous system (SoNS). The ANS is the part of the nervous system that controls visceral function below the conscious level, while the SoNS is the part of the nervous system that is associated with the voluntary control of body movements through skeletal muscles [1].

In some conditions, the impairment in communication between brain and motoric muscles can be happened because of an accident, disease or congenital disablement. For example, Amyotrophic Lateral Sclerosis (ALS) disease causes disability in controlling body movement although there is no functional problem with the brain itself as the central command.

In this research, SoNS will be examined in thorough detail by reading brain signal patterns obtained by using an Electroencephalogram (EEG) as shown in Figure 1. EEG is a device that is able to capture brain signals by placing electrodes on the scalp (non-invasive method). Besides this non-invasive method, there is another method to acquire brain signals by placing electrodes directly on the brain surface (invasive method) called Electrocorticography (ECoG), or Intracranial Electroencephalography (iEEG). For the sake of simplicity, non-invasive methods are usually preferable to invasive. The accuracy of EEG readings is not vastly different between these methods [2]. However, the invasive method is more accurate because the electrodes are positioned nearer to the brain, which is better than the external method at eliminating noise signals that can disturb the readings of the brain signal patterns.

Using brain signal patterns, a computer application can be developed to help people who are paralyzed or have a motoric disability to use and control a computer, as well as type on a keyboard.

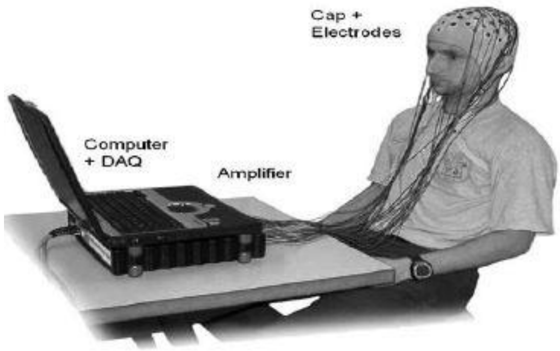

Figure 1.Components of a typical BCI system

II. RESEARCH METHOD

A. EEG and Brain Signals

As the central command for the human body, the brain has complex activities that generate many signals. The accuracy of brain signal acquisition depends on many factors, including whether external or internal methods are used. For external factors, the reading of brain signals relies on the sensitivity of the EEG electrodes and the number of channels. Each EEG electrode has a sensitive sensor to capture certain ranges of brain signals, measured in cycle per second or Hertz (frequency) [5]. There is a correlation between sensor sensitivity and accuracy. The more sensitive, the more frequency ranges can be identified. Of course, the term frequency here is not only referring to signal frequency, but also noise frequency. The noise frequency could be minimized later by signal processing and filtering, from simply applying gel to each electrode to minimize impedance, to more complex digital filtering methods [6].

The number of channels is also important, since more EEG channels will acquire more signals from many parts of the brain. EEG devices are divided into several classes, from the cheapest low-density EEG, which consists of an EEG sensor array with only two channels (left and right side), to more expensive high-density EEGs which consist of an EEG sensor array of up to 256 channels. An experiment conducted by Lau et al. showed that a 35-channel EEG is sufficient to classify two dominant electrocortical sources [7]. For a multi-class classifier, the use of more channels would improve the results [8]. In this research, a 12-channel EEG could be used as an alternative in an empirical approach to gain average accuracy when using a cheaper device.

On the other hand, there are internal factors that could influence the readings of EEG patterns as well. These internal factors could arise from the activity of the brain itself. In a normal active condition, Beta β) signal which resides around 16–31 Hz. A beta (β) signal will be more active in a stressful condition or when trying to speak out loud, which causes the release of cortisol. In a rest or sleep condition, the dominant human brain signal is an alpha (α) signal (8–15 Hz) and a theta (θ) signal (4–7 Hz), respectively, as shown in Figure 2-4. These frequencies are emitted when people are relaxed, in a good mood, or sleeping, causing the release of serotonin. However, an α block occurs when an α signal disappears when a person is thinking, blinking, or stimulated in a different way, such as audio and visual stimulation. Physiological signals are spontaneous and less controllable. With the growing interest in Brain-Computer Interface (BCI) and Electroencephalogram (EEG) users have also been considered [9]. Therefore, for a BCI application, a β signal is the main frequency that should be examined because people need to focus and concentrate when interacting with a computer.

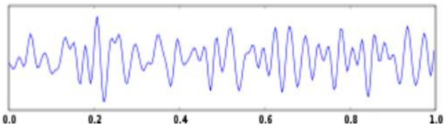
Figure 2. Beta (β) signal

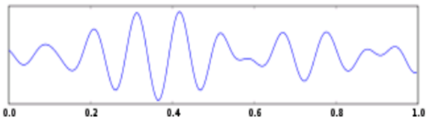
Figure 3. Alpha (α) signal

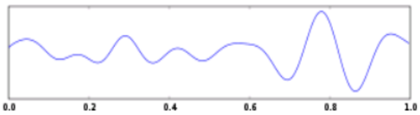
Figure 4. Theta (θ) signal

In addition to the internal factors mentioned above, one more factor could affect the readings of brain signals. The movement of the head, eyes, eyelid, face muscles, or any other body parts could cause some frequency fluctuation in brain signals [10]. In the present research study, the brain signal pattern will be classified into specific activities needed to control the computer, for example to move an object on the monitor or to move the cursor. To ensure good and precise classification, the brain signal will be induced by stimuli. By using stimulation, the expected brain signal pattern could be more accurately classified in relation to a specific computer task. Motor Imagery and Steady-State Visually Evoked Potential (SSVEP) are the most common methods used to stimulate a brain signal pattern in a BCI application.

B. Motor Imagery

Motor Imagery is a popular and simple method that is used to trigger a brain signal pattern by visualizing the movement of some body parts. Practicing Motor Imagery refers to engaging in a mental practice for how to do a physical task using one’s imagination, not an actual physical movement.

Based on research, the Motor Imagery method has been widely used to mentally engage in skilled tasks, such as sports, dance, music, and even surgery. Utilizing Motor Imagery would have nearly the same effect as doing an actual physical practice. This is because the brain activity that is triggered in Motor Imagery and physical activity is similar. However, Blankertz et al. [11] concluded that one of the challenges in Motor Imagery for BCI is the significant inter-subject variability with respect to the characteristics of the brain signals.

Moreover, people with a motor disability or who are paralyzed cannot move their body limbs. However, because their central nervous system is still functioning well, they can use this Motor Imagery method to control the machine or computer, not by using their hands or other body parts, but by using the brain signal patterns captured by an EEG device and translated into a specific task in the form of digital data.

For example, visualizing a right-hand movement will stimulate a specific brain signal pattern to be classified into a particular computer task, such as moving the cursor to the right, and vice versa. Again, imagining walking forward will stimulate a specific brain signal pattern to be classified into a particular machine task, such as moving the wheelchair forward.

The advantage of Motor Imagery lies in its simplicity. There is no need to add any auxiliary devices for the brain signal stimulation process. However, the drawback of this method is the need for adaptability. Not all people find it easy to engage in Motor Imagery the first time they try it; this is especially true for people that do not have a physical disability and who often engage in physical and logical activities instead of visualization. Lack of focus and an inability to visualize an activity smoothly could deteriorate the performance of the brain signal feature extraction. Intensive focus and great effort are needed to do a long consecutive Motor Imagery, which can result in dizziness, nausea, and fatigue.

C. Steady State Visually Evoked Potentials (SSVEP)

SSVEP is another brain signal stimulation method that uses visually-evoked stimuli. SSVEP is a popular paradigm for a BCI due to its robust presence in EEG signals. This method uses a person's eyes as the receptors of stimuli, in the form of moving animation or screen flickering. Unlike Motor Imagery, SSVEP uses a monitor as an external medium to trigger the brain signal pattern. SSVEP is evoked when a visual stimulation is repeated and the reaction to a subsequent stimulus occurs before the effect of the previous stimulus has subsided [12]. Among the various BCI paradigms, SSVEP has been shown to be very useful for many applications as well as cognitive and clinical research studies (e.g., visual attention, working memory, epilepsy, and brain rhythms) [13].

For some users, SSVEP is easier than Motor Imagery because SSVEP uses external stimuli to build the brain signal pattern. SSVEP is suitable for people whose eyes are still good enough to serve as the receptors of the visual stimuli. In a SSVEP-based BCI, the first problem faced is selecting the type of stimulator to use. Many types of stimulators can be used to evoke SSVEP, including a cathode ray tube (CRT) monitor, a liquid crystal display (LCD) monitor, or a light-emitting diode (LED) array. Because of the different lighting mechanisms, these stimulators can be used in BCI systems with different complexities [14]. The drawback of this method is that it requires an auxiliary monitor device with an adequate screen size and a proper distance between the screen and the user. A screen that is too small or too large will distract the focal point of the users and deteriorate the accuracy of the classifier. The distance between the screen monitor and the user could also affect the accuracy of the classifier [15].

In an SSVEP, the monitor is used to show the moving animation; for example, a left arrow moving from right to left. The user focuses on this animation and, consequently, the brain emits a specific signal pattern to be classified into a specific computer task. The monitor is also used to show some flickering objects in specific frequencies, usually in low frequency, for example four flickering objects in 5, 6, 7, and 8 Hertz (Hz), respectively. Then, the user focuses on one flickering object at a time. Thus, the brain will emit a frequency that is similar to the frequency emitted by the flickering object.

III. RESULT AND DISCUSSION

This study's goal was to determine the better method of motor control to be used in brain-controlled interface (BCI) systems. The two motor control methods tested were Motor Imagery and steady state visually evoked potentials (SSVEP). These motor control methods were tested using the software, OpenVibe 2.0.1. OpenVibe is an open source software platform used for BCI and real-time neurosciences. An electroencephalogram (EEG) device was tested using EmotivEpoc+, which features fourteen EEG channels plus two reference channels. The software Emotiv SDK Premium Edition v3.3.3 was used to develop communication between the EmotivEpoc+ device and OpenVibe Software.

In order to get objective results, both experiments used the same scenario for feature extraction and classifier algorithm. Common Spatial Pattern (CSP) was used as the feature extraction algorithm and Support Vector Machine (SVM) was used as the classifier algorithm. Figure 5 shows a block diagram of the BCI system.

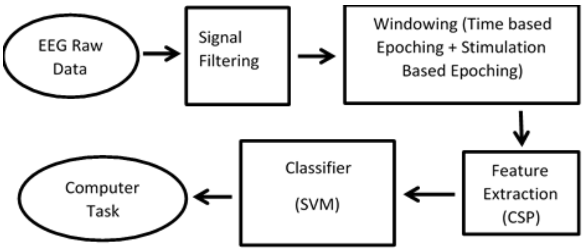

Figure 5. Block diagram of the BCI system

When testing Motor Imagery, users were asked to imagine left-hand movement as a command to move the cursor to the left side and also to imagine right-hand movement as a command to move the cursor to the right side. Brain signal pattern was acquired by the EEG device, then filtered by band-pass filter to minimize the frequencies caused by noise. Once the brain signal patter was filtered, the signal entered a windowing process to tag the time periods when stimulation events occurred. Further, the tagged signals were processed by feature-extraction to optimize the distinction between both signal patterns before being classified by a trained SVM classifier into respective cursor movement.

When testing the SSVEP system, the same scenario was used. The only difference was the use of visual stimuli. This test used two flickering objects shown on a monitor, at the frequencies of 7 Hz and 12 Hz. These were used as brain signal stimulation for cursor movement command to the left and right side, respectively. To elicit an SSVEP, a Repetitive Visual Stimulus (RVS) must be presented to the user. The RVS can be rendered on a computer screen by alternating graphic patterns, or with external light sources able to emit modulated light. Table 1 shows the results of the testing from twenty-sequence commands, with a two-second resting state between each sequence.

Table 1.
The result of Motor Imagery and SSVEP experiment

Sequence	Command	Motor Imagery	SSVEP
1	Neutral	Neutral	Neutral
2	Left	Left	Left
3	Right	Left	Right
4	Neutral	Neutral	Neutral
5	Left	Left	Left
6	Neutral	Right	Left
7	Right	Right	Right
8	Left	Left	Left
9	Neutral	Neutral	Neutral
10	Left	Left	Left
11	Right	Left	Left
12	Neutral	Neutral	Neutral
13	Left	Left	Left
14	Neutral	Left	Neutral
15	Right	Left	Right
16	Neutral	Right	Neutral
17	Left	Left	Left
18	Right	Left	Left
19	Left	Left	Left
20	Neutral	Neutral	Neutral
Error Percentage		35%	15%

Based on the results shown in Table 1, SSVEP is shown to be a more accurate method of brain-signal stimulation with a fifteen percent error rate, compared with Motor Imagery, which has a thirty-five percent error rate. Both methods are shown to be less accurate when there were two or more consecutive commands, as seen with sequences six, eleven, and eighteen. The results also show that the two-second resting state between sequences is insufficient time to allow the brain signal to neutralize before the next command. A longer resting state could improve the accuracy, but it will increase delay time to send a command. The accuracy could also be improved by tuning the parameter of CSP as feature extraction and SVM as classifier.

IV. Conclusion

BCI is a solution for people with motoric disability to interact with computer through brain signal as a command. One of challenging works in BCI is how to interpret brain signal into particular computer task. Whilst brain signal is very susceptible to many factors, both from internal and external, that can affect the accuracy of brain signal pattern recognition. Signal filtering and processing could be done to remove noise signal and improve detected signal. CSP and SVM as feature extraction and classifier to classify brain signal pattern into computer task.

In order to evoke brain signal, there are 2 most common method to be used in BCI application, i.e. Motor Imagery and SSVEP method. In designing this type of BCI, the aspects involved should be taken into consideration systematically. For example, a very complex method may conduct a very good accuracy, but it is time-consuming, which makes the system un-timely. In this situation, we should select a suitable accuracy and speed to make a better system [16]. Motor Imagery is the simpler one since this method does not need auxiliary device and use user’s imagination to generate brain signal pattern. Even this is the simpler method, not all people are easy to implement this method.

SSVEP is a response of the vision to a light stimulus, the electric activity focuses at the vision cortex, mainly at the primary vision cortex, which locates at the occipital area. SSVEP uses flickered screen monitor to evoke the brain signal with the same frequency. Indeed, this method is not as simple as motor imagery because the need of screen monitor with proper screen size and distance. But this method is easier to be implemented because the stimuli are assisted with external device. As the result, the accuracy of SSVEP (15 percent of error) as brain signal stimulation is more accurate than Motor Imagery (35 percent of error).

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