A review on elicit potentials in the brain to recognize Brain-Machine interface

Mohd Rizwan Jafar¹, Ashish Kumar Srivastava²
¹Atria Institute of Technology, Bangalore
²G.L. Bajaj Institute of Technology and Management, Greater Noida

Email:- mohd.rizwanjafar@atria.edu

Abstract. Brain-machine interface is a technique with the help of which a user can generate a control signal to operate a machine by manipulating its state of cognition. In this technique, electrical signals generated in the central/peripheral nervous system are used to generate commands to interact with machines. In this paper, authors reviewed this technique in detail to find out the state of the art. This paper is written in such a way that a beginner can understand what a brain machine actually is. In this paper different types of methods to elicit signals for brain machine interface is explained along with different types of methods to record the signals. It is also described the state of the art in feature extraction and classification methods used in brain machine interface.

Keywords: Brain Machine Interface, SSVEP, ERD, ERS, MI, Motor Imagery

1. INTRODUCTION

Brain-machine interface (BMI) or brain-computer interface (BCI) is a technique with the help of which a user can generate a control signal to operate a machine by manipulating its state of cognition [1-3]. In this technique, electrical signals generated in the central/peripheral nervous system are used to generate commands to interact with machines [4]. The electric signals in the brain are produced when neurons communicate with each other. All the information flows in the central and peripheral nervous system with the help of neurons [5-8]. This information is in the form of electrical signals. Every neuron fires a pulse of electric current known as the action potential. This action potential works as a piece of information for the other neuron which is connected to this neuron. Every neuron has a fixed baseline rate of firing an action potential, but the frequency of firing can be increased or decreased based upon the information received [6]. For an excitatory stimulus the baseline firing rate increases while for an inhibitory stimulus the baseline firing rate decreases. This increase and decrease in action potential contribute to the generation of different waveforms of electrical potential for different kinds of stimulus inside the nervous system [8-10]. The potential generated by a single neuron is very less which can not be measured on the scalp, but when a large number of neurons fires action potential it can be easily recorded from the scalp.

2. METHODS

The methods which can be used to elicit potentials in the brain can be categorized in the following manner [1].
Event-related to potentials.

Steady state visually evoked potentials

Event related synchronization/Desynchronization

Hybrid BCI

Event related BCI is generated by a sudden event like flashing of a light or unexpected new stimuli presented to a subject. This sudden change is represented by the several positive and negative peaks in the waveform of the signal. One most commonly used method of generating event related potentials is P300. In this method a matrix is used. This matrix contains letters and numbers in rows and columns. Each row and column is flashed alternatively and the user has to concentrate on the flashing of the letter or number which he wants to select. This generates event related potentials in the brain. This P300 method is highly sensitive to Inter-stimulus intervals (ISI) and the matrix size. Inter-stimulus interval is the interval between the offset of one stimuli and the onset of the other. Farwell and Donchin in 1998 reported that the classification accuracy was higher when larger ISI was taken, while later on in 2002 meinickel et al. reported that shorter ISI contributed to high classification rates.

Matrix-Size are a wide variety of matrix sizes that have been used in literature. The matrix of size 3*3, 4*4, 6*6, 8*8 and 12*12 have been used. The 6*6 matrix is the most commonly used matrix. It recent studies it has been reported that that 3*3 matrix has higher classification accuracy and higher bit rate as compared to 3*3 matrix [7].

The steady-state visually evoked potentials of BCI repetitive visual stimuli, are presented to the user. When a user focuses on the stimuli an SSVEP is generated in the brain. This generated potential has a frequency equal to the oscillating component, whose frequency is equal to the frequency of the repetitive stimuli presented to the subject. The frequency of the repetitive visual stimuli is kept in the range of 1-100 HZ [3]. One disadvantage associated with these types of systems is that the repetitive visual stimuli at certain frequencies can cause elliptical seizures in patients. There are a lot of ways in which we can provide repetitive visual stimuli. But mainly it is of three main types i.e. light stimuli, single graphic stimuli, and pattern stimuli. When light is used as a stimuli, a certain kind of light is flashed at the subject. This light has a particular known frequency. In a single screen stimuli graphics like rectangle, squares, arrows are used which are displayed on the screen at a particular frequency. While in pattern reversal stimuli systems oscillatory alternations of graphical patterns are used. These patterns are displayed on the screen which is placed in front of the subject. The patterns displayed on the screens are checkboards, linerboards colored in black and white. LED’s when used as a stimuli has a median bit rate of upto 42 bits a minute, single pattern stimuli has a median bit rate of upto 32.075 bits a minute, while a pattern reversal system has a median bit rate of upto 26 bits a minute [6].

In the Event related Synchronization and Desynchronization, when the brain is in the condition of rest, it produces synchronized oscillations while when a movement is imagined it produces desynchronization. When we think of a task the waveform generated in our brain is less synchronized as compared to the rest state. The task which a subject imagines can be moving of voluntary organs, like limbs, tongue etc. During the imagining of a task the desynchronization occurs in the waveform of the frontal cortex [8]. This kind of BCI was one of the most commonly used methods from 2007 to 2011.

Hybrid BCI methods in which two or more kinds of BCI are used simultaneously. It helps us in achieving better results. This kind of BCI can be categorized into spontaneous and sequential BCI. If the signals are processed separately and the two BCI processes are arranged in a series then this is sequential BCI, while then the two processes are arranged in parallel it is called spontaneous BCI. The entire process of brain machine interface is described in Figure 1
2.1. Recording of potentials

The potentials can be recorded by placing the electrodes surgically inside the brain or by placing them on the scalp. The signals recorded from the surgically placed electrodes have better quality as compared to the signals recorded from the scalp. Although prima facie surgically placed electrodes look a better choice but it is not used a lot by the researchers. The scalp method is most commonly used because of the risks associated with the surgical methods. Based upon the position of the electrodes and the number of recording sites the potential recording methods can be categorized. The classification is described in Figure 2.

**Figure 2**- Methods to Record potential for Brain Machine Interface
2.2 Pre-Processing, Feature Extraction and Classification

Generally, researchers use signals in the range of 0.1-100 Hz for the classification. Researchers have used signals in the range of 0.1-40 Hz [8], 0.1-45 [11], 0.1-35 [12], 0.1-60 [5]. In different researches, artifacts from eye blinks, electrical supply etc. should also be removed from the data too, in order to achieve a better accuracy of classification. Feature extraction is a process of removing dimensions from the data. In this process the data is analyzed to find out a criterion by the help of which it can be classified easily. Researchers have used a wide variety of methods to extract features from the data and classify them. These methods include Fast Fourier Transformation [9-10], Discrete Wavelet Transformation [8, 11, 26], logarithmic band power features [12-15], minimum energy method [10], Power spectral density and HHT [5-7] for the extraction of features, while for classification purpose Support vector machines, neural networks, Linear discriminant analysis, Bayesian classifier and Genetic algorithm are the most common type of methods used [8-12]. Table 1 describes the combination of feature extraction and classification methods used in the literature.

| S. No. | Feature Extraction          | Method of classification         | Ref.       |
|-------|----------------------------|---------------------------------|------------|
| 1     | Discrete Wavelet Transformation | Artificial Neural Network (ANN) | [1]        |
| 2     | Fast Fourier transformation  | (ANN)                           | [2]        |
| 3     | Fast Fourier transformation  | (ANN)                           | [3]        |
| 4     | Logarithmic band power      | Linear Discriminant Analysis    | [4-5]      |
| 5     | PSD and HHT                 | Genetic Algorithm and (ANN)     | [6-8]      |
| 6     | Band Power Features         | (ANN)                           | [9-10]     |
| 7     | Averaging Method            | Support vector machine          | [12]       |
| 8     | Minimum Energy Combination  | Support Vector Machine          | [13]       |
| 9     | Wavelet Transformation      | Support Vector Machine          | [14]       |
| 10    | Band Power Method           | Linear Discriminant Analysis    | [15]       |

3. CONCLUSION

Power spectral density was the most commonly used method during 2007 to 2011 for feature extraction. But later on other methods like wavelet transformation also gained popularity among the researchers. Similarly, during 2007 to 2011 LDA followed by SVM was the most common technique for the classification of signals, but later on other techniques like Artificial neural networks gained prevalence. The most common type of signal which was used between 2007 to 2011 was Steady state visually evoked potentials, but later on Motor imagery gained prevalence. Currently Hybrid BCI is the most efficient method for BCI applications. If we have a constant bit rate, the general trend is that if we try to increase the number of choices for the classification, the efficiency and speed of the classification will decrease. A robust BCI system needs to have a large number of choices for the classification without affecting the speed and accuracy of the system. As per current literature hybrid BCI appears to be the prominent contender to achieve that.

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