The Research of EEG Brain-Computer Interface Drive Technology

Chao Zhang [a], Ji Zou

School of Electronic and Information Engineering, Chang Chun University, Chang Chun, China

[a]157075018@qq.com

Abstract

A novel method created on thought based brain signal and it has been technologically advanced rapidly. The Brain control system is a rapidly emerging multidisciplinary study area which has perceived remarkable achievement over the past few years. In this paper, we review the background, feature extraction and classification algorithms used to design the Electroencephalography (EEG) based Brain-Machine Interface to control the mobile robots.

Keywords

Multi-modal; Electroencephalogram(EEG); Brain Computer Interface(BCI); Motor Imagery(MI); Steady State Visual Evoked Potential(SSVEP).

1. Introduction

BRAIN-COMPUTER interfaces (BCIs) or Brain-machine interfaces (BMIs) or Brain-control systems are communication devices which enable users to send instructions to computers or other external devices using brain signals. This is a rapidly developing multidisciplinary research field which has perceived impressive accomplishment over the past few years. In another word, this kind of systems are called as Human machine integration control systems that does not depend on the brain‘s normal output pathway of peripheral nerves and muscles and it is purely relies on human thoughts and thinking by providing a new communication channel with the outside world. It has been effectively applied in an extensive range of fields such as biomedical, computer science, neuroscience, physiology, rehabilitation, engineering and healthcare disciplines. The EEG based BCIs consists of electrodes placed in various positions on the scalp surface area to monitor the subject brain and extract the specific features from the brain electrical signals that reflect the thoughts or intention of the subject, and translates their intentions into action. These signals are generally categorized as delta (1- 4 Hz), theta (4-7 Hz), alpha (8-12Hz), mu (8-13 Hz), beta (12-30 Hz), and gamma (range greater than 30Hz). The delta rhythms occur in deep, dreamless sleep and theta rhythms occur in high emotional conditions, or in deep meditation and light sleep stage.

The alpha rhythm happens in a state of physical and mental relaxation, when the eyes are closed. The beta rhythm pattern is desynchronized and the condition is the normal awake open eyes, normal waking consciousness and a sensitive state of alertness, logic and critical cognitive. The gamma rhythm can be acquired from somatosensory cortex and mu rhythm from sensor motor cortex.

Author: Zhang Chao, male, 37 , Associate professor

The contract number: 20150204039SF

Project source: Jilin province Department of science

Project name: Based on the modal rehabilitation wheelchair drive key technology research of eeg signals

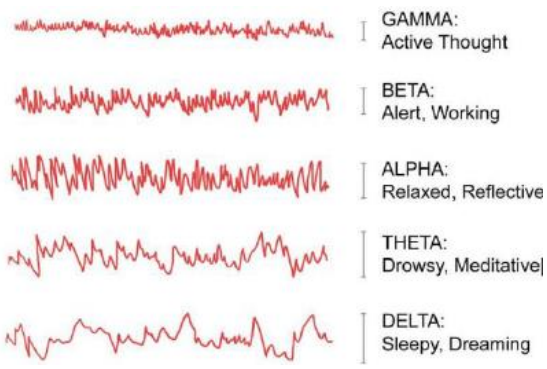

Fig.1 Brain waves under various states

Brain signal activities are detectable in three ways depending on the placement of electrodes such as Electroencephalogram – EEG (noninvasive), Electrocardiogram – ECoG (partially invasive – cortical surface), and intracortical recordings (invasive). In an invasive method of brain signal acquisition, electrodes are neurosurgical implanted either inside the brain (intracortical) or on the brain surface (cortical surface). Most of the invasive researches have been done with rats and monkeys; however, certain experiments with humans have also been done. In noninvasive method, the electrodes that detect and measure the brain signals are placed on the surface of the scalp. The advantages of using noninvasive method are portable, safe, reasonably low-cost and easy to use also. Other than EEG, based on research intensive, alternative noninvasive BMI methods are also available such as magneto encephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared systems (fNIR) and blood-oxygen-level dependent (BOLD). Every technique has certain advantages and disadvantages compared to other techniques. The EEG has been widely used in both research and clinical purposes because of its portability and inexpensiveness.

2. Bci Background

Electroencephalography (EEG) has a history of more than 100 years and it is still undergoing massive progress of research that contributes in many disciplines. Luigi Galvani, an Italian physician first demonstrated in his research that the nerves contain an intrinsic form of electrical activity in 1791. Based on these theories and scientific facts many researches have been done for years and researchers have identified that these signals are actually generated from the brain. In 1875, Richard Caton, an English physician has discovered the existence of electrical signals from the brains of animals such as monkeys and rabbits. Later in 1920s, a German neurologist, Hans Berger measured traces of brain electrical activities on the human scalp and named this electrical activity as "Electroencephalogram". His observations in human brain signals reported in his first set of papers in 1929, he sought to identify the factors were involved in the EEG signal development in the brain and was able to conclude that the EEG was related to activity within the brain and other parts of the human body. The origin of ―alpha rhythm‖ was first identified by Adrian and Matthews in 1934 during their study. In 1938, Jasper and Andrews used the term gamma to refer to the rhythms of above 30Hz and theta rhythms were introduced by Wolter and Dovey in 1944. In 1964, Dr. William GreyWalter, neurophysiologist and robotician have first described BCI. He has fixed electrodes on the motor parts of the patient‘s brain and that patient was asked to press a button to advance the projector slide. The patient‘s brain activity in that movement is recorded. Then a system is connected to the projector and he has successfully advanced the slide just by the brain signal without pressing the button.

Brain-computer interface research was actively started during 1970s. In 1973, the first publication of BCIs by Vidal, computer science department and brain research institute, University of California, Los Angeles who developed BCIs system based on visual evoked potential. In 1978, William N. Kuhlman had identified in his research on feedback training of the mu rhythm which can be recorded over human somatosensory cortex in the absence of movement. In 1988, there was a significant development in EEG based spelling device used P300evoked potential which was developed by Farwell and Donchin.

In 1991, Wolpaw developed a new EEG based 1dimensional control communication model which uses 8 –12 Hz mu rhythm to move a cursor from one point toanother point in a straight line. The extension of this research, Wolpow has developed a 2 dimensional cursor movement in 1994. Furthermore, these years, the number of BCI research teams gradually increases their size and even more now.

After many years of research in this area, BCI has grown to an advanced level and it is found to be very useful in many ways for those who are physically disabled. As the world now is growing with advanced technologies, BCIs has gained more attention and new objectives achieved in many different areas such as rehabilitation or hands-free gaming. In general, Neural-interface system, also known as BMIs and neuroelectronic user devices in particular, are still in their infancy.

3. Eeg Signal Processing Methods Used for Feature Extraction

The ultimate objective of BMI or BCI is to convert the brain signals into actions; those actions are either software or hardware oriented. By mere thinking of writing text via a virtual keyboard on a screen is the example of software oriented, and to control or monitor a mobile robot is a worthy example of hardware oriented. To convert the brain signals into actions, either regression or classification algorithms can be used. The classification and feature extraction is crucial; because unwanted or irrelevant features can cause poor performance of the action translation algorithm, increase the complexity of controls and performance accuracy. The feature extraction is the initial phase during the data acquisition of bioelectrical signals and it is a process extracting the silent characteristics of the signals followed by signal classification. To obtain specific information or differentiate the mental task from EEG signals are obviously called as feature extraction. Depends on activity, a few neurons may adequate to control a BMI system and such neurons are called grandmother neurons. The main objective of this paper is to review the different artificial neural network classification and feature extraction algorithms used in EEG-based BCI or BMI research. Alternatively, this review is affording recommendations to the researchers for selecting the best suitable classification algorithm for their BCI research.

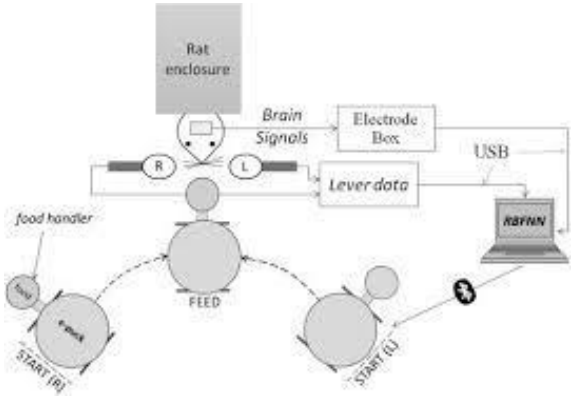

Fig.2 Rat's brain signals based robot controller system

In a recent work E. Iáñez et al. discuss in detail about electroencephalography (EEG) based one degree of freedom robot arm control. Wavelet transform algorithm with DB2 filter has been used for signal discriminator, which can perform better than FFT algorithm and multilayer perceptron (MLP) neural network has been used as a classifier. The developed system has been achieved the best results.

Hazrati et al. used adaptive probabilistic neural network (APNN) for EEG signal classification in an interactive online real-time BCI environment. Monopolar EEG signals were recorded by using the electrodes placed according to the international 10-20 system from the scalp. The EEG signals were filtered with a 0.5-45 Hz bandpass filter. Especially the eye blink and movement signals were collected separately from the right and left earlobe channels. These signals were collected constantly and continuously thought-out research which gives the subject free from eye blinks and eye movement.

According to Medl et al., they have proposed EEG based robotic hand activities by using the Fuzzy Neural Network (FNN). Like Medl et al., Zhan et al. also proposed an EGG based robotic hand activities by using the back propagation (BP) network for the Fuzzy Neural Network (FNN) model. Alomari et al. employed two machine learning algorithm such as neural network (NN) and support vector machine (SVM) to achieve the EGG classification results of 89.8% and 97.1% respectively for executing the left and right hand movements. Noninvasive method of EEG data signal acquisition was done through the 64-channel electrodes according to the international 10-20 system (excluding some electrodes). They have used MATLAB toolbox filtering and automatic artifact removal (ARR) for preprocessing stage. After the ARR process, EEG data were epoched by extracting data epochs and independent component analysis (ICA) for artifacts removal.

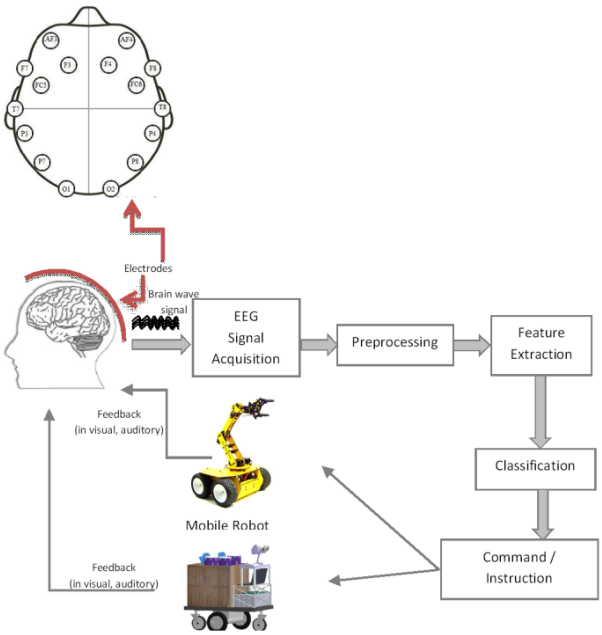

Fig.3 Components of Brain Machine Interface system

4. Conclusion

Studying biomedical signals are an significant research area and it has an rapid advancement not only for the physically challenged but also it helps common people. In this paper, we review different data acquisition techniques, algorithms for feature extraction and classification of EEG signals. However, based on our analysis either neural network or support vector machine is the best choice for EEG classification technique with high accuracy results depends on the application requirements. Besides, the hybrid-BCI (hBCI) system - combine brain and other biosignals such as electromyographic (EMG) and electroencephalographic (EEG) with P300 protocol or steady state visually evoked potentials (SSVEP) or combination of neural network algorithm or SVM could be the definitive system for future requirement.

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