AN APPLICATION OF ELECTROENCEPHALOGRAM SIGNALS CLASSIFICATION FOR CONTROLLING A MOBILE ROBOT

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ABSTRACT

This paper introduces a method of using electroencephalogram (EEG) signals classification to identify human mental activities. These human mental activities are associated to five different commands in order to activate these movements (neutral, forward, backward, left, and right) of a mobile robot. This paper uses Emotiv-EPOC device to acquire the raw EEG data. Besides, a graphical user interface is built to permit the users to control the mobile robot in real time. In this research, a new model of Modular Multi Net (MMN) are proposed. This MMN carries out the comparison between two models of classifiers: Multi-Layer Perceptron neural network (MLP) and (MMN). In generally, the process to classify the EEG signal includes three main steps. First, the raw EEG data is preprocessed to filter noise and remove DC offset from Emotiv-EPOC device. Then, a number of appropriate features are extracted by using Fast Fourier Transform (FFT). Finally, an Artificial Neural Network (ANN) is used to classify five different human mental activities. The final average accuracy of the classification process with 5 mental activities trained simultaneously is 30.68%.

KEYWORDS: *Electroencephalography (EEG), Brain computer interface (BCI), Brain machine interface (BMI), Emotiv EPOC headset, Mind control, Mobile robot.*

1. INTRODUCTION

In the last decades, along with the evolution of technologies and computational methods, the development of interfaces between humans and machines, especially in the field of robotic control based on EEG signal, has been expanding. The robotic control system through EEG signal, is also called non-invasive Brain computer interface (BCI) system, has opened a new period for technology. Recent researches have showed that BCI systems have led a large number of advantages to the field of medically disabled patients (Chowdhury, et al. (2014)). People who are partially or totally paralyzed (e.g., amyotrophic lateral sclerosis (ALS), also known as Lou Gehrig's disease, or brainstem stroke) or have other motor disabilities cand find a BCI as an alternative communication channel (Wolpaw, et al. (2000)). In addition, BCI systems are used to augment people's communication capabilities, provide new procedures of education and entertainment, and also enable the operation of physical devices (Barbosa, et al. (2010)).

BCI systems are divided into two classes: dependent and independent.

A dependent BCI use arising signals in reaction to external stimulation. In denpendent BCI systems, the generation of EEG signal depends on gaze direction of user or flicker frequency of the stimulation (Wolpaw, et al. (2002) and Holewa & Nawrocka (2014)). Karolina Holewa and Agata Nawrocka built a BCI system based on Steady Stated Visual Evoked Potentials (SSVEP), in their project, a LED panel with LEDs flashing at different frequencies (28 Hz, 30 Hz, 32 Hz, and 34 Hz) is implemented, when the user focuses on a selected frequency, SSVEP are generated and have the same frequency with selected LED, then BCI sent the corresponding commands to Lego Mindstorms robot (Holewa & Nawrocka (2014)).). In another project, by combining SSVEP and a multi layer feedforward neural network, Manyakov's group increased the number of stimulation up to 16 while high accuracy is maintained with the small window size (Manyakov, et al. (2011)). BCI based on SSVEP have a high accuracy and do not require a long time for training user skill. At present time, although the dependent BCI can still be useful, it does not give any new method to generate EEG signal other than dependence on gaze direction and flicker frequency of the stimulations. Moreover, contacting with highly frequent LED in a long time can cause a number of eye problems.

An independent BCI use directly conscious signals from brain for controlling an application, independently from external events (Wolpaw, et al. (2002)). Ouyang's group built an independent BCI to control a robotic arm. In order to increase accuracy of BCI, they used Independent component analysis algorithm (ICA) to extract features, then using these features to apply to a MLP (Ouyang, et al. (2013)). Alternatively, Barbosa's group used ensemble of MLP (Barbosa, et al. (2010)). In general, The accuracy of independent BCI systems are lower than dependent BCI. Nevertheless, the independent BCI provides a large number of methods to control, such as: recognization of rhythms which are related to imagination of movements or recognization of rhythms in specific frequency bands (Barbosa, et al. (2010)). Furthermore, for people with the most serve neuromuscular disabilities, independent BCI systems are likely to be more useful (Wolpaw, et al. (2002)).

In this paper, an independent BCI, which is shown in Figure 1, is proposed to control a mobile robot. Moreover, a GUI is built in order to connect BCI to mobile robot by classifying differently mental activities and sending the corresponding commands to activate the robot in real time.

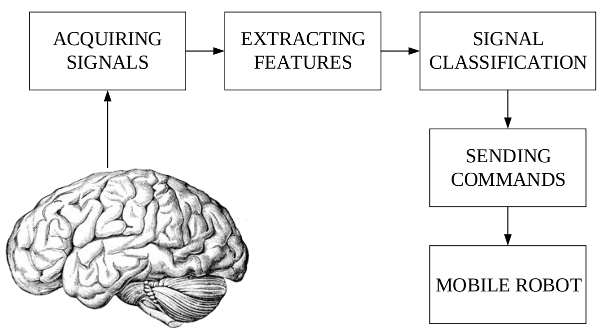


Fig 1. Overall BCI system diagram

This paper is organized in seven section. Section 2 introduces basic rhythms of EEG and specifications of Emotiv EPOC. Section 3 depicts how signals have been preprocessed and features have been extracted, followed by Section 4, which presents architecture of MLP and classifies EEG signal by applying features to MLP. Section 5 proposes an architecture of MMN, while Section 6 describes a mobile robot and GUI that allows user controls the mobile robot. Finally, Section 7 discusses the conclusions of this paper and shows a comparison of classification accuracy between MLP and MMN.

2. EEG BACKGROUND

An EEG signal is a measurement of currents that flow during synaptic excitations of dendrites of many pyramidal neurons in the cerebral cortex. Signals have amplitudes of 0.5 – 1.5 mV and up to several millivolts for spikes. However, on the scalp, the amplitudes commonly lie within 10 – 100 µV (Sanei & Chambers (2007)).

2.1 EEG rhythms

There are six major brain waves, which are shown in Table 1, distinguished by their different frequency ranges (Sanei & Chambers (2007)).

Table 1. Basic rhythms

Rhythm	**Bandwidth** (Hz)
Delta (δ)	0.5 – 4
Theta (θ)	4 – 7.5
Mu (µ)	8 – 12
Alpha (α)	8 – 13
Beta (β)	14 – 30
Gamma (γ)	30 and over

In these kind of rhythms, mu and/or beta rhythms could be good signal features for EEG – based communication (Wolpaw, et al. (2002)). Therefore, these frequencies are chosen to be processed.

2.2 Emotiv EPOC device

The Emotiv EPOC headset is one of inexpensive EEG devices, this device containing 14 measuring electrodes and 2 reference electrodes. All these electrodes are arranged according to the international 10 – 20 system. Figure 2, which is mapped by EEGLab software, shows 14 measuring electrode positions on scalp.

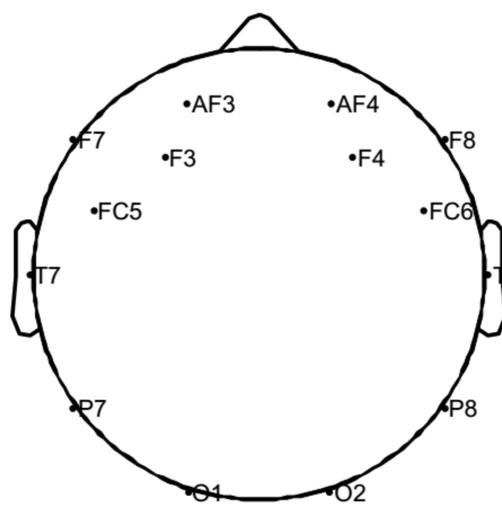


Fig 2. 14 measuring electrode positions

The device operates at the sampling rate at 128 Hz, with 14 – bit resolution. Although these specification shows that the EPOC device offer dataset which is slightly worse than a standard EEG using the international 10 – 20 system, the EPOC is extremely inexpensive compared to a standard EEG, and is capable for applying to a number of BCI systems.

3. PREPROCESSING

The electrical signal of brain activities is so weak and it is extremely sensitive to noises, which is also known as non-neural physiological signals (Zhang, et al. (2015)). The non neural physiological signals, such as electromyogram (EMG), electrooculogram (EOG), electrocardiography (ECG), and space elelectromagnetic noises during the acquition process, make the analysis of EEG data much more difficult or even can be misread as the physiological phenoma of iterst (Wan, et al. (2016)).

Therefore, EEG signals should be eliminated noises before being extracted features in order to improve the operation of the BCI system.

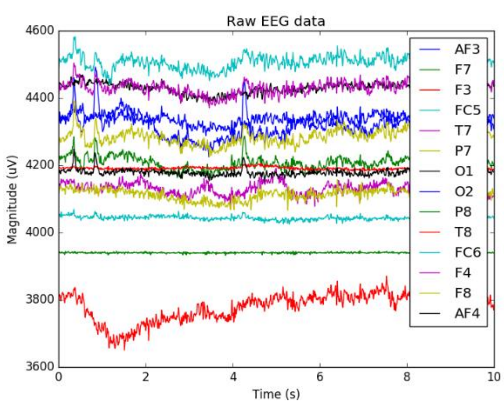
3.1 Prefilter

In this paper, only electrical noise and EOG artifacts are detected and removed from signal. Attributes of these noises is shown in table 2.

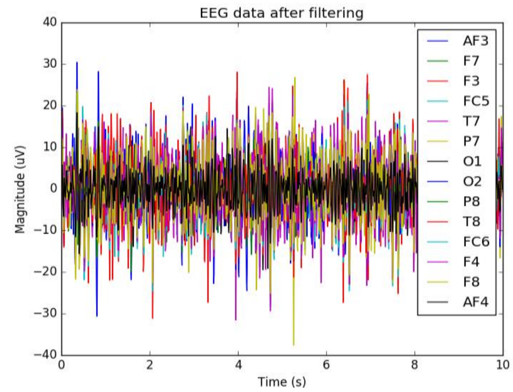
Table 2. Interferences

Interferences	Attribute
Electrical noise	- Generated from power line and other noises from electrical device. - Appears in high power spectrum (35 Hz or over).
EOG Artifact	- Generated from eye blinking and eye rolling. - Appears in low power spectrum (1 – 10 Hz) (Zhang, et al. (2015)).

Because this paper uses EEG signals with frequency range from 8 Hz to 30 Hz, a Butterworth digital band pass filter with 8 Hz high pass cut off frequency and 30 Hz low pass cut off frequency is applied to signal in order to eliminate interferences. Figure 3 describes EEG pattern before and after being prefiltered.



(a)



(b)

Fig 3. An EEG pattern before filtering (a); And an EEG pattern after filtering (b)

3.2 Feature extraction

A few features such as mean, zero – crossing and energy from different rhythms of signal are normally used as feature vector inputs for MLP. This paper uses energy of alpha, beta rhythms, and whole EEG spectrum as input of MLP. The energy is defined as:

$$E = \frac{1}{L} \times \sum_{i=a}^{b} A_i^2 \qquad (1)$$

where (a, b) is the frequency range of rhythm, L is the length of signal windowing, and A is magnitude of signal corresponding to each frequency.

4. MULTI LAYER PERCEPTRON

Once EEG signals have been preprocessed in the computer to generate feature vectors, they are applied to MLP in order to be classified. In this paper, a series of 10 trials is carried out for each of the five state: forward, right, backward, left, and neutral to obtain 10 datasets, totalling 50 samples. Each sample is acquired within a period of 10 seconds, including information from 14 channels. From this dataset, each dataset will be trained by MLP and then be tested with the other 9 dataset.

4.1 Architecture

An MLP neural network, is shown in Figure 4, consists of 3 layers: input, hidden, and output layer.

The input and output layer depend on the extracted features and the purpose of applications. In this paper, the feature vector input has 42 elements which is received from extracting 3 bands per each of 14 channels. The output vector has 5 elements corresponding to 5 states of robot movement. The classification is obtained as the one with higher output value.

The hidden layer nodes is chosen by experimenting or using Genetic Algorithm. Theoretically, the more nodes hidden layer has the lower cost function is and the better BCI syystem operate. However, using too many hidden nodes wastes time on training process without a relevant decrease the percentage error significantly. Therefore, in this paper, the hidden layer of MLP uses 50 nodes.

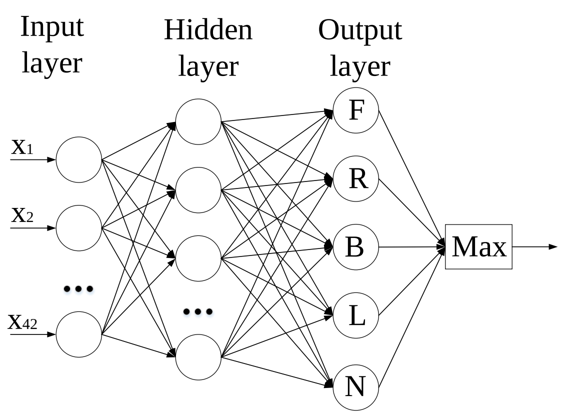


Fig 4. Architecture of the MLP neural network

4.2 Cost Function

There are two cost function are frequently used in classifier is Mean Square Error (MSE) and Minimum Classification Error (MCE). MCE usually produces classified results better than MSE. However, MCE based classifiers are certainly difficult to implement while classifiers by using MSE can approximate discrete values as close as possible (Chow & Cho (2007)). Therefore, this paper uses MSE, is defined in formula (2), as cost function.

$$E = \frac{1}{m}\sum_{i=1}^{m}(y-y)^2 \qquad (2)$$

where m is dimension of dataset, y is desired output, and y is approximately output.

4.3 Training

There are many optimization algorithms are used for the purpose of adjusting weights so that MSE function converge to 0. The simplest way to adjust weights is to use a constantly learning rate throughout the whole training process. However, in order to have an effective classifier, the change of learning rate is neccessary.

Many reasearchers have proposed rules for automatically adapting the learning rate. These rules control the speed of convergence by increasing or decreasing the learning rate based on the error (Lecun, et al. (1998)). This paper uses L – BFGS, which is a algorithm using one of adaptive learning rate rules, for optimizing MSE. L – BFGS optimizes the cost function by finding learning rate based on the Wolfe conditions and searching direction based on approximately Hessian matrice. In addition, L – BFGS overcomes the disavantages of the other quasi Newton method about hardware memory by maintaining simple and compact approximation of Hessian matrices instead of storeing fully dense $n \times n$ approximations (Nocedal & Wright (1999)).

4.4 Testing results

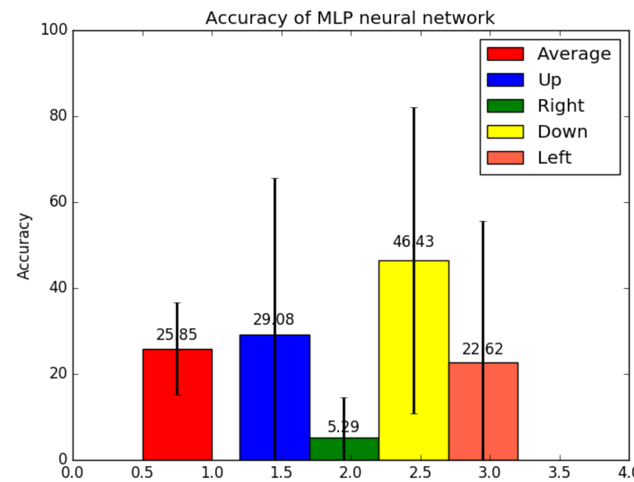


Fig 5. Accuracy of MLP

5. MODULAR MULTI NET

5.1 Architecture

This paper proposes an architecture of MMN based on the project of Barbosa's group (Barbosa, et al. (2010)). In this system, four MLP neural networks are used, see Figure 6.

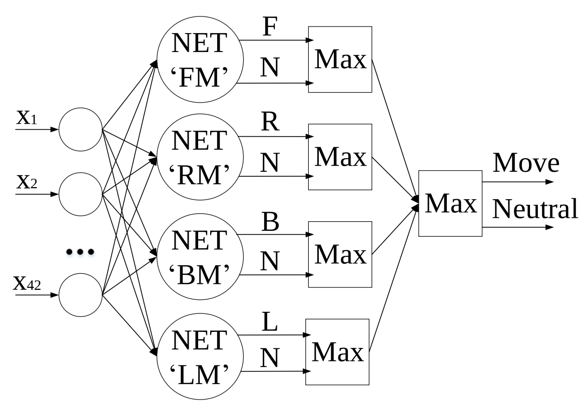


Fig 6. Architecture of MMN

Each MLP classifies feature vector into movement corresponding to network or neutral state through the first 'max' layer.

In the second 'max' layer, if more than one network classifies a feature vector into movement, the classification will be obtained as the one higher output value. In the other hand, if all network classifies a feature vector into neutral, the classification will be obtained as neutral.

5.2 Testing results

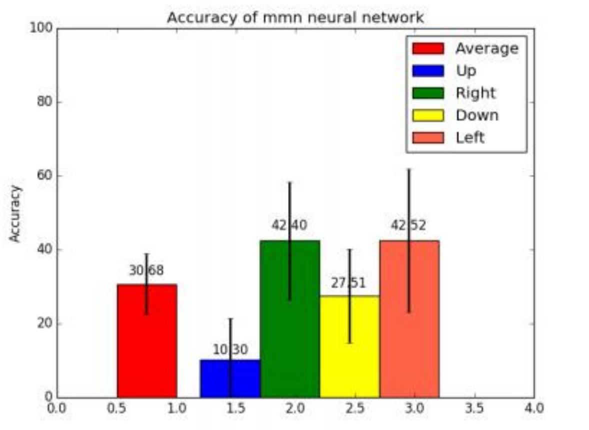


Fig 7. Accuracy of MMN

6. BRAIN COMPUTER INTERFACE

6.1 Mobile robot

To validate the proposed classifier, the BCI is applied to a 3 – wheeled mobile robot, see Figure 8. The communication with robot is made through a HC06 Bluetooth module, which receives characters from computer and translates it into commands to activate the robot.

Fig 8. Mobile robot

6.2 Graphical user interface

The GUI is implemented under Python environment, c containing two tabs: Training and User. In training tab, data is acquired from EPOC device by using Emotiv's API, preprocessed, and processed. In user tab, GUI support a number of options to communicate with the robot.

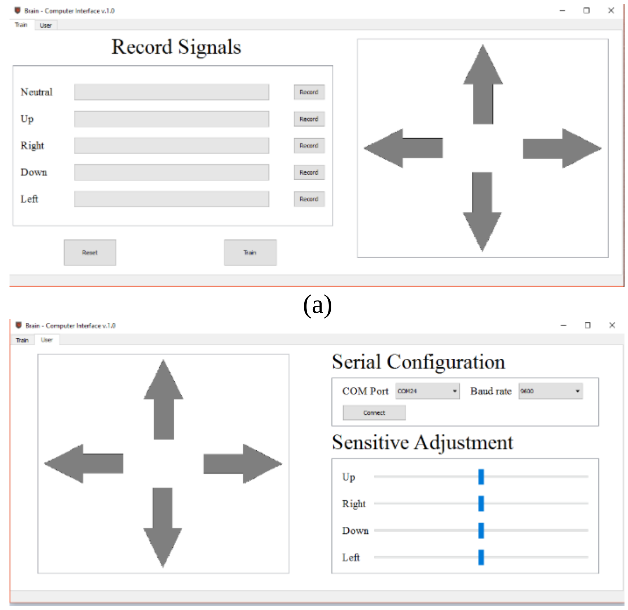


Fig 9. Graphical user interface, including: Tab train (a) and Tab user (b)

7. CONCLUSIONS

The results in Figure 7 and 8 show that the average accuracy of MMN is 30.68% while the average accuracy of MLP is only 28.85%. For MMN, the accuracy of states is equivalent and its dispersion is lower than MLP. For MLP, the accuracy of one or two states are significantly higher than the others. These comparison suggest that the proposed MMN model operate effectively more than the MLP in classifying multi outputs

In the paper, a GUI is built which allows user control robot with the maximum is 5 movements in real time. In this GUI, user can decrease the number of robot movements to increase the average accuracy. Moreover, the accuracy of classifier can be increased by developing maintaining user skill.

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PHOTOS AND INFORMATION

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