Một ứng dụng của Internet of Things sử dụng hệ thống giao tiếp não-máy tính để hỗ trợ người khuyết tật

An Internet of Things application based on Brain-Computer Interface for supporting handicap people

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Abstract
Trong bài báo này, một hướng tiếp cận mới của Internet of Things (IoTs) sử dụng hệ thống giao tiếp não-máy tính được đề xuất nhằm hỗ trợ những người khuyết tật. Về mặt tổng thể, đề tài của chúng tôi có thể được chia thành hai phần chính. Ở phần thứ nhất, chúng tôi xây dựng một hệ thống giao tiếp não-máy tính để chuyển đổi các tín hiệu điện não (EEG) thành các câu lệnh điều khiển. Quá trình chuyển đổi này bao gồm ba bước chính. Đầu tiên, các tín hiệu EEG thô thu được sẽ được tiền xử lý để lọc nhiễu và loại bỏ DC offset từ thiết bị Emotiv-EPOC. Tiếp theo, các đặc tính thích hợp sẽ được khai thác để tạo thành vector đặc tính cho thuật toán phân loại. Cuối cùng, một mô hình của mạng thần kinh nhân tạo được đề xuất để phân loại vector đặc tính thành các câu lệnh điều khiển để điều khiển thiết bị IoTs. Ở phần thứ hai, chúng tôi xây dựng một hệ thống IoTs cho phép người sử dụng kích hoạt chuông báo động trong nhà hoặc gửi tin nhắn đến số điện thoại của người thân để thông báo họ đang cần sự giúp đỡ. Kết quả thực nghiệm cho thấy độ chính xác cao nhất của hệ thống với ba trạng thái điều khiển được huấn luyện đồng thời là 71.85%.

Keywords
Brain-Computer Interface (BCI), Emotiv-EPOC Headset, Internet of Things (IoTs), GSM.

Tóm tắt
In this paper, a new simple approach of IoTs application using Brain computer interface (BCI) is proposed to support for handicap people. In general, our project could be divided into two parts. In the first one, we build a BCI system to translate electroencephalogram (EEG) signals into different control commands. The process for decoding the EEG signals contains three main steps. Beginning with the raw EEG data is preprocessed to filter noises and remove the DC offset from Emotiv-EPOC device, followed by a number of appropriate features are extracted, and culminating in a model of Artificial Neural Network (ANN) is proposed to identify three different mental activities which are associated to three different commands for the purpose of controlling IoTs devices. In the second one, an IoTs system is constructed to permit users to activate an alarm bell or send a message to the cell phone of their relatives (in case of nobody is home) so as to indicate that they are in urgent need of help. The average classification result of system with three mental activities trained simultaneously is 71.85%.

Symbol

Symbol	Unit	Meaning
p	W	The power of signal
m		The length of the signal's window

Chữ viết tắt

IoTs	Internet of Things
EEG	Electroencephalography
EOG	Electrooculography
ECoG	Electrocorticography
BCI	Brain-Computer Interface
SSVEP	Steady Stated Visual Evoked Potentials
IM	Imaginary Movements
ANN	Artificial Neural Network
DWT	Discrete Wavelet Transform
MLP	Multi-Layer Perceptron
MMN	Modular Multi Net
LA	Left Arm
RA	Right Arm
GUI	Graphical User Interface

1. Introduction
BCI is a new field of research that is aimed at building a communication between human brain and computer, which allow people to control devices through EEG signals. BCI systems can be categorized as invasive, which uses ECoG electrodes to record signals from the surface of brain or intracortical electrodes to record neural activities within the brain, or non-invasive, which records signals from the scalp [12].
In the last decades, along with the evolution of technologies and computational methods, BCI has been successfully being applied in wide fields. Holewa and Nawrocka built a BCI system based on Steady Stated Visual Evoked Potentials (SSVEP) in order to control a Lego Mindstorms [6], the BCI system of Barbosa's group classified imaginary movements to activate a mobile robot [3], Wu's group developed an Android 3D racing game which is controlled by BCI

based on mental states such as attention and meditation [13], to name but a few. Especially, a number of researching groups have been focusing on building BCI systems which can be used for 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 as an alternative communication device [5]. For instance, a BCI-based assistive robot arm, which is developed by Arnil's group, assists people who has no arm [2], or a brain-controlled wheelchair which is built by Xie and Li [14].

Meanwhile, the effect of IoTs on technology has been dramatically increasing. A number of researchers began to embed BCI system in IoTs applications for the purpose of medical problems. Yong and Ho built a system that stream brain and physiological signals in real time to the cloud in order to support neuroscience applications such as neuroergonomics, BCI, and cognitive training [15]. In addition, Buyser's group combined smart glass and EEG headset to control IoTs appliances in the smart home. In their project, the object the user want to control is detected by using smart glass and then triggered by commands from EEG headset [4]. Though recent researches showed that BCI system have led a large number of advantages to the field of medicine, it has not yet been widely applied in life because of its limitation on tasks and the expense of EEG devices

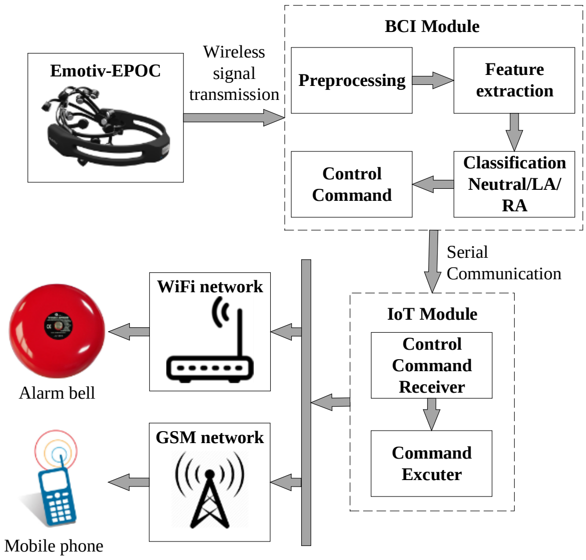


Fig. 1 *Overall system of our proposed system*

In this paper, we propose a simple IoTs application using non-invasive motor imagery BCI as introduced in Fig. 1 in order to support the care of paralyzed or disabled people at home. In our system, BCI is used to classify three specific mental activities of handicap people: neutral, imaginary movements (IM) of left arm (LA) and right arm (RA). These activities are associated to control commands which are sent to IoTs module to activate the corresponding IoTs device. Therefore, the handicap people could use this system to announce to their relatives whenever they need help. This allow families to reduce the time spent on patient careness.

Overall, this paper is organized into nine sections. Section 2 introduces basic rhythms of EEG signals, then section 3 shows information about specifications of Emotiv-EPOC device. Section 4 depicts how signals are preprocessed, followed by section 5, which presents feature extraction of signals after preprocessing. Section 6 proposes an architecture of MMN for classification tasks, while section 7 describes an IoTs application of BCI. Afterwards, some experimental analysis results with data collected from a healthy male are illustrated in section 8. Finally, section 9 discusses conclusions of this work.

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. There are six major brain waves, which are shown in Table 1, distinguished by their different frequency ranges [9].

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/alpha and beta rhythms could be good signal features for EEG – based communication [12]. Therefore, these frequencies are chosen to be processed.

3. Emotiv-EPOC device

The Emotiv EPOC headset is one of inexpensive EEG devices. This device includes 14 measuring electrodes and 2 reference electrodes. All electrodes are arranged according to the international 10 – 20 systems. Fig. 2, which is mapped by EEGLab software, shows 14 measuring electrode positions on a scalp.

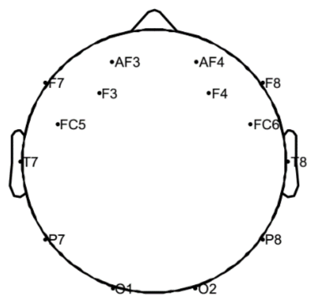


Fig. 2 *Overall system of the Emotiv Epoc*

The device operates at the sampling rate at 128 Hz, with 14 – bit resolution. Limitations compared to standard EEG devices on collecting dataset notwithstanding, the EPOC price is considerably lower. As a result, the EPOC is capable for applying to the large number of BCI systems.

In this paper, because imaginary movements are used to classify, only electrodes located near the motor cortex area (F7, F3, F4, F8, FC5, FC6, T7, T8) are chosen to acquire EEG signals instead of the use of all electrodes of device. This help to gradually reduce the processing time.

4. Preprocessing Process

The electrical signal of brain activities is feeble and extremely sensitive to noises, which are also known as non-neural physiological signals [16]. Some of these signals can be listed as: electromyogram (EMG), electrooculogram (EOG), electrocardiography (ECG). And, the space elelectromagnetic noises during the acquisition process makes the analysis of EEG data become much more difficult or even can be misread as the physiological phenomena of interest [11]. Consequently, EEG signals should be eliminated interferences before being extracted features in order to improve the operation of the BCI system. In this paper, only electrical noises and EOG artifacts are detected and removed from signal. Attributes of these noises are shown in Table 2.

Table. 2 Basic rhythms

Interferences	Attribute
Electrical noises	- Generated from power line and from electrical device. - Appear in high power spectrum (50 or 60 Hz).
EOG Artifacts	- Generated from eye blinking and eye rolling. - Appears in low power spectrum (1 – 10 Hz) [16].

Additionally, because we only use the 10 – 30 Hz band of the EEG signal, a Butterworth digital band-pass filter with cut-off frequency of 10 – 30 Hz is applied to signal in order to eliminate interferences. Fig. 3 describes EEG pattern before and after being pre-filtered. In which, the blue and orange line denotes the signal before and after filtering, respectively.

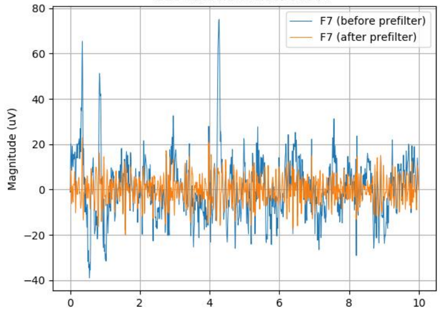


Fig. 3 *An EEG pattern before and after filtering*

5. Features Extraction

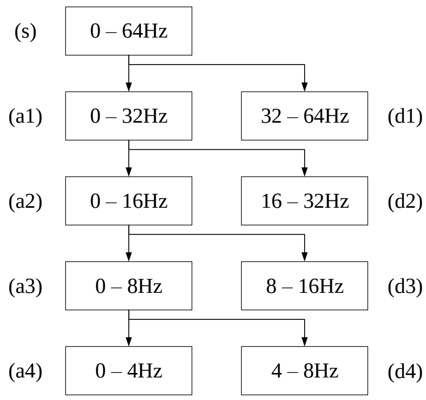


Fig. 4 *DWT decomposition of frequencies range*

To extract features from the pre-filtered EEG signals, it must be decomposed using Discrete Wavelet Transform (DWT) at first. Because the signals are sampled at 128 Hz, the decomposition of frequency ranges begin in the range between 0 and 64 Hz. The number of levels of decomposition which is chosen based on the dominant frequency components of the signal. In this paper, the level of 4 and the wavelet of Daubechies order 4 is chosen [7, 8, 10] to approximately represent basic rhythms of brainwaves in Table 1, see Fig. 4.

After decomposition, a few features such as mean, median, or energy from different levels of DWT is extracted to create feature vectors for classifier [3, 8]. In this paper, we chose power which does fairly good job in transferring EEG signals from time domain into spectral domain [1]. The feature vector is composed by the power of d3 (approximate mu band), d2 (approximate beta band), and a1 (approximation of whole useful EEG spectrum). The power is defined as

$$p = \frac{1}{m}\sum_{i=0}^{m}\left|x\ i\right|^{2} \qquad (1)$$

Where i is the index of numerical data, with i = 1, 2, 3, …, m; and m is the length of the window

6. Classification Process

MLP is one of the most popular classifiers which is used in BCI. From experiments, we see that MLP solves the 2-class BCI classification problems well, but it is not effective in multitask classification. Therefore, we propose an architecture of MMN based on the project of Barbosa's group [3] to classify 3 mental activities as illustrated in Fig. 5.

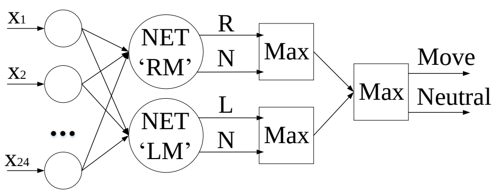


Fig. 5 *Architecture of MMN*

In this MMN, two MLP neural networks are used, each MLP classifies feature vector inputs into movements corresponding to network (i.e left/right) or neutral state through the first 'max' layer. In the second 'max' layer, if more than one network classify the feature vector into movement, the classification result will be obtained as the one higher output value. On the other hand, if all network classifies a feature vector into neutral, the classification will be obtained as neutral.

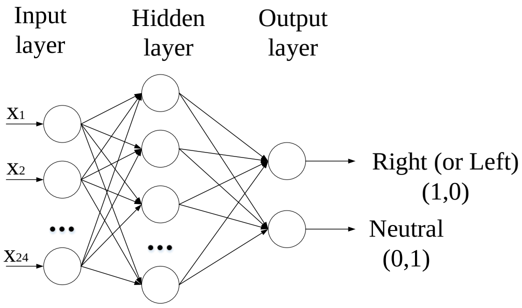
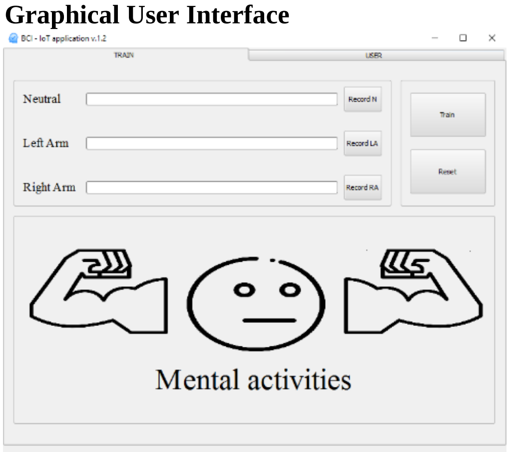


Fig. 6 *Architecture of MLP*

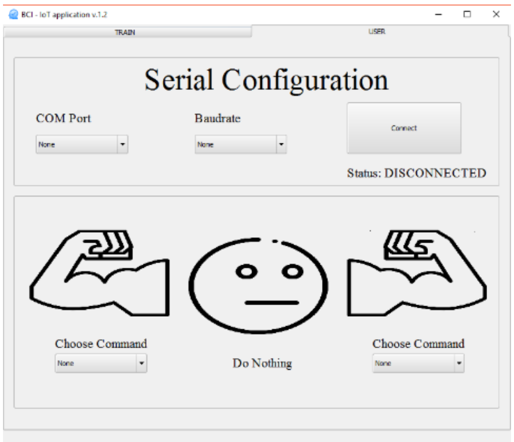
Each MLP, shown in Fig. 6, consists of 3 layers: input, hidden, and output layer. The input and output layer depend on the extracted features and the purpose of applications. In this paper, the feature vector input has 24 elements which is received from extracting 3 bands per each of 8 selected channels. The output vector has 2 elements corresponding to 2 states of robot movement (move or stay). 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 system 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.

7. IoTs application

7.1 Graphical User Interface



(a)

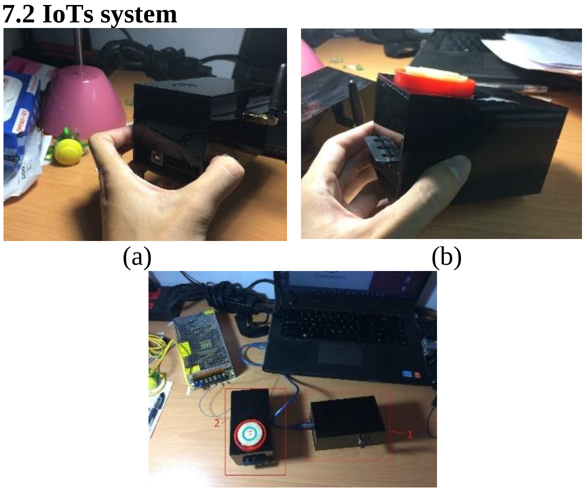


(b)

Fig. 7 *Graphical User Interface (a) "Train" Tab, and (b) "Use" Tab*

The GUI is implemented under Python environment contains two tabs: "Train" and "Use". In the "Train" tab, data is acquired from Emotiv-EPOC device by using Emotiv's API, then preprocessed to extract features which are used to implement feature vector inputs for the process of training classifier. In the "Use" tab, the GUI supports a number of options to communicate with the IoTs control system.

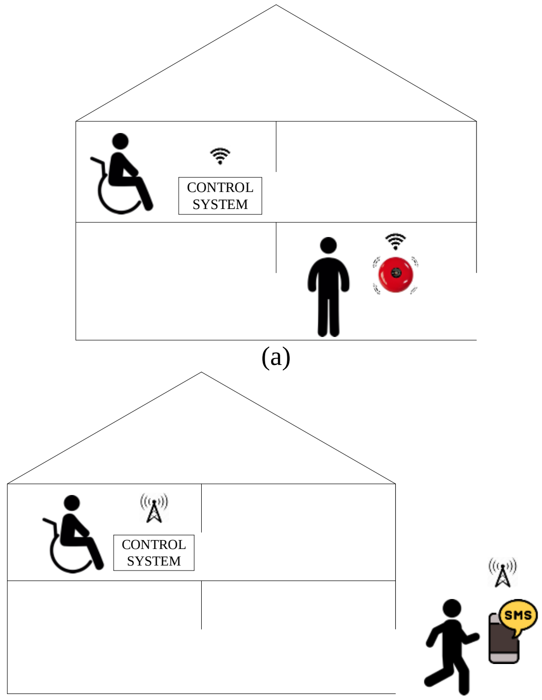
7.2 IoTs system



(a) (b) (c)

Fig. 8 *IoTs system*

The IoTs control system (see Fig. 8c) including a control module, as shown in Fig. 8a, and an alarm module, as shown in Fig. 8b, can be handled through Wi-Fi network. By which, the handicap people can activate the alarm bell anywhere in their house and whenever they are in need of help (see Fig. 9a).
In addition, the IoTs control system is also connected to GSM network. This allow the handicap people to send a SOS message to the mobile phone of their relatives in the case of nobody is at home (see Fig. 9b).



(b)

Fig. 9 *The IoTs application based on BCI*

8. Experimental Methods and Results

Our experiments are conducted on a 22-years old healthy man. The participant is required to record 50 trials to collect 50 datasets. Each trial contains two tasks which correspond to recording of neutral and imaginary movements of LA and RA. Each task is recorded in the period of 15 seconds using the program TestBench provided by Emotiv company. To test the classification results of the BCI system, 15 datasets are chosen randomly to train the MMN and the rest is used for testing procedure. The classification results are illustrated in Fig. 7

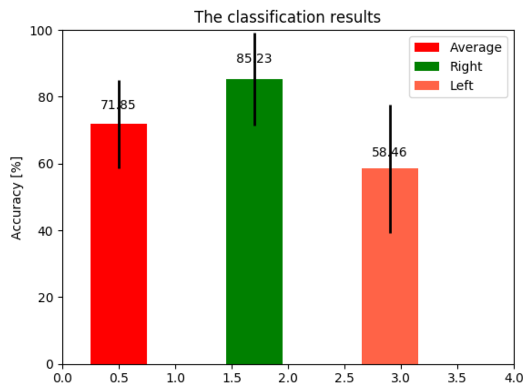


Fig. 10 *The classification results*

9. Conclusions

This paper propose an IoTs application which is based on non-invasive BCI to support handicap people. In which, we built a control system including a control module which is connected to a computer and an alarm module. Besides, a GUI was designed to allow user to send control commands to the controlling module in real time.

The experimental results show that the average classification result of our system can reach at 71.85 % with standard deviation of 11.49 %.

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