

Building a brain wave system for patient supports

Thanh Ha Nguyen, Thi Mai Thuong Duong, Toan Luu Van, Phuong Huy Nguyen

Abstract— This paper proposes a method of design a brainwave communication system that supports patient to engage more effectively in their daily life. The system recognizes some basic requests of patients such as eating, drinking, sleeping, using the toilet, turning on / off the lights, turning on / off the TV, from which directly controls the device and / or notify caregivers.

Index Terms— Brain-Computer Interface Systems, Multilayer perceptron, Wavelet transform, Patient supports

I. INTRODUCTION

According to 2019 disability statistics annual report, about 6.2 million Vietnamese people had a disability, in which: severe disability 31%, mobility impairment 20%; cognitive or learning disabilities 19%. Although these data may not fully and accurately reflect the actual data of people with disabilities in Vietnam, they, to some extent, has shown that disability and people with disability are challenges in national socio-economic development [4].

For people with congenital disability, due to the accident or seizure, many of them completely lose their ability to move their limbs, others even lose the ability to communicate. All activities, including personal hygiene, depend entirely on the care of a relatives or doctors. However, the inability to move and use language causes many difficulties for caregivers to understand and care of them. Socially, people with this kind of disability completely lose their ability to participate in normal social activities such as travel, family economic support, and study. In the next coming years, the number of people with disabilities tends to increase due to traffic accidents, labor accidents and environmental pollution, while the causes of disability also fluctuate and are different than before.

Thus, there is a need to research and develop a system to support communication with patients, the elderly or people with congenital disabilities. The system must be easy to use and operate without the help of any other person. To do this, first of all, it is necessary to decode some basic requests in the communication and activities of people with disabilities through brainwave, then design a system to support the implementation of these requests. Patients who are paralyzed, unable to move their body and unable to communicate can use thoughts to make a number of requirements such as turning

on/off the light, turning on / off the TV (automatically controlling the system) or eat, drink, sleep, go to the toilet, call a caregiver via the speaker or smart phone.

II. MATERIAL AND METHODS

1. Hardware design

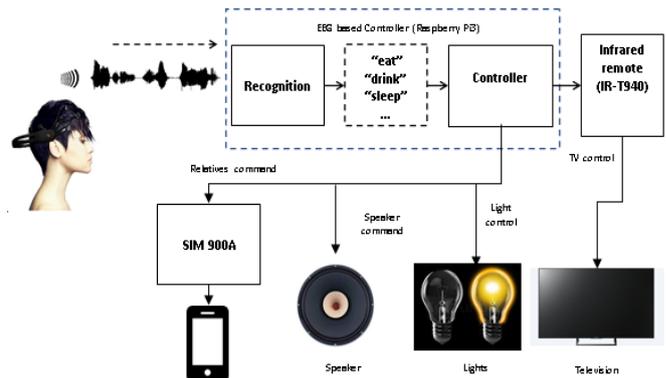


Fig 1. Brainwave communication system for patient supports

Figure 1 describe brainwave communication system. In which, the system hardware includes:

- Eloc+ (Emotiv) headset

Patient thought recognition records the EEG data using mobile Emotiv EPOC++ headset. This headset has 16 electrodes located based international standard for 10-20 electrodes system. In which, 14 electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and 2 reference electrodes. EPOC+ headset is moistened to increase the conduct ability [3].



Fig.2. Emotiv Eloc+ headset and 16 electrodes location

EEG signal include many different spectrum components. The magnitude of EEG signal is in the range from 10 to 100 μ V. Bandwidth of EEG is limited and the most important frequencies, in the physiological point of view, in the range from 0.1 to 30Hz. Clinical bands of standard EEG signal are delta (0.1 to 3.5Hz), theta (4 to 7.5Hz), alpha (8 to 13Hz) and beta bandwidth (14 to 30Hz). EEG signal with frequency higher than 30Hz is called gamma signal 0.

Thanh Ha Nguyen, Thai Nguyen University, Thai Nguyen, Vietnam, +84913073591

Thi Mai Thuong Duong, Department of Computer Science, University of Information and Communication Technology, Thai Nguyen, Vietnam, +84945373858

Toan Luu Van, The North – eastern College of Technology, Agriculture and Forestry, Lang Son, Vietnam, +84978580613

Phuong Huy Nguyen, Department of Electronics Engineering, Thai Nguyen University of Technology, Thai Nguyen, Vietnam, +84912488515

▪ EEG based Controller

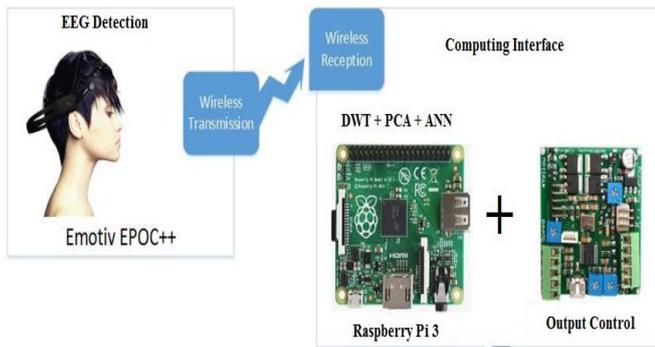


Fig 3. EEG based Controller

This controller fundamentally is a Raspberry pi3 microcontroller with software installed to receive EEG signal from Emotiv EPOC+ headset, decompose signal, decode to commands and send to output I/O modules. Raspberry pi 3 is a mini computer, so it is easier to implement the opensource applications which communicate with I/O.

▪ Bluetooth and IR communication module

Receive the command from the signal analyze and synthesis module, convert to Bluetooth and IR signals and send to the devices. The Raspberry Pi 3 has an integrated Wi-Fi and Bluetooth adapter. IR-T940 Infrared remote module is dedicated for controlling the TV.



Fig 4. IR-T940 Infrared remote module

▪ Lamp control module

To control lamp states, Raspberry Pi will work as a controller and a set of relays will be in charge of power path. We use relay module as shown in Figure 5, which includes 4 extra small relays.

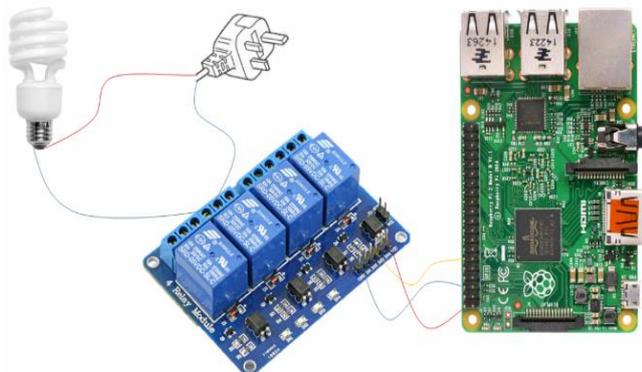


Fig 5. Relay Module for turning on / off the lights

▪ Speaker command

The Raspberry Pi is a mini computer so the speak out loud implement is simple. The audio files are available in Pi. When the software recognizes the patients' requests, these files will be active and the speaker will give a voice to call the relatives.



Fig 6. Speaker command module for relative calling

▪ Mobile communication module

This module is active when the patient wants to call the relatives (who can not hear the speaker). Simply, we use Module Sim900A.



Fig 7. SIM900A Module for mobile phone communication

2. Software design

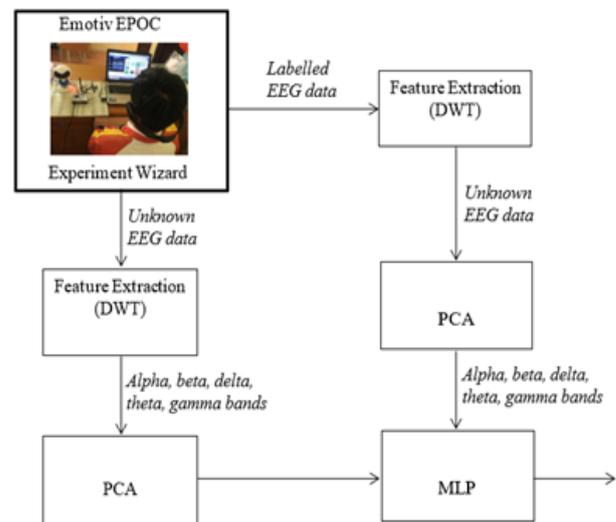


Fig 8. Diagram of functions in control software

Control software is installed in Pi3 to receive the EEG signal from Emotiv EPOC+ headset, extract the features of the EEG signal using Wavelet, reduce the signal dimension of feature vector using Principal Component Analysis (PCA) method, classifies these signals using neural network MLP, decode to command and send to communication modules [4].

▪ EEG signal receiving

We use Emotivpro tool to collect the raw EEG signal from Emotiv EPOC+ headset. This software is useful for experiment design, prepare and config multimedia. Software is also able to collect the EEG signal structurally and systematically.

- Extract the EEG signal feature

There are many ways to extract signal feature EEG effectively. One of them is Wavelet transform. In this paper, we use discrete Wavelet transform. With this method, each signal from electrode will be decomposed into 5 fundamental signal components: Delta, Theta, Alpha, Beta, and Gamma.

According to datasheet, the EPOC+ headset collect the signal with 128Hz frequency. Hence, DWT analysis level is 5 (Table 1) to get the basic waveforms. Besides, there are many ways to choose wavelet family, however, in this paper, we choose Wavelet Daubechies4 family to process EEG signal. From the fundamental wavelet component, we calculate characteristic parameter for classifying emotions: signal mean, power, and standard deviation. With total 14 electrodes we get feature vector including 210 parameters.

Table 1. Wavelet Decomposition of EEG signal

Decomposition levels	Sub-band Decomposition	Frequency bands	Frequency bandwidth
1	CD1	Noise	64-128
2	CD2	Gamma	32-64
3	CD3	Beta	16-32
4	CD4	Alpha	8-16
5	CD5	Theta	4-8
	CA5	Delta	0-4

- Reduce feature vector dimension using Principal Component Analysis method

The dimensions of feature vector obtain after Wavelet transform of EEG signal are 210. If provide this vector to MLP network, the training time is really long. Besides, in 210 parameters, there are some parameters having insignificant impacts to the others. So, we use principal component analysis method to reduce the feature vector dimensions to 70.

- EEG signal identification using MLP network

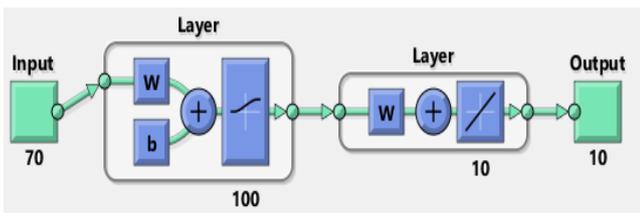


Figure 9. The MLP architecture for EEG identification

To achieve a high performance of the patient support system, we have to find not only a good method to extract the feature of EEG signal but also a suitable technology to decomposition. In fact, there are some basic decompose technologies widely used: Euclidean Distance Decomposition, Support Vector Machine – SVM, artificial neural network-based decomposition. With the support of GPU, Deep Learning technique, artificial neural network-based decomposition technology shows the preeminence [10], [9]. For this reason, we use MLP network with the structure shown in Figure 9.

During the training period, EEG signal is labeled, that is, the data from a patients' request recognized, is recorded and sent to MLP network to train the thought recognition model.

During the identification period, undetermined EEG data is provided to trained MLP network to give the best decision of the command. The number of neurons at input layer equal to the length of the input feature vectors. We tested to determine

the best configuration for neural network about: the number of neurons at hidden layer and epochs as follows:

- The number of neurons at hidden layer are 100.
- The number of epochs in learning period are 1000.
- Active function used is sigmoid, learning ratio is 0.1.

Training network stops when the number of epochs reach to 1000 or mean squared error reach to such a small value as 0.001.

Each thought command (eat, drink, sleep...) is trained 250 times for one person. EEG signal length for each training sample is 10 seconds. Recorded data is divided into sets with 80% is for training network and 20% for testing. So, each command corresponds to 200 samples for training network and 50 samples for testing the accuracy of identification.

III. RESULTS AND DISCUSSION

We successfully design both hardware and software for patient support brainwave communication system. This system can recognize 10 patients' requests as: eat, drink, sleep, using the toilet, turn on/off light, turn on/off TV, call for relatives, neutral.

For identification implement, patients look to the figures on the interfaces, think in 10 seconds to make samples for training neural network process. Samples are relatively calculated to the previous samples, give the recommendation for the patient to decide which identification sample is correct. After training full 200 samples for each command, patient will test 50 times and evaluate results.



Fig10. The actual architecture of the patient supports system

The results of 50 testing data samples listed in Table 2. These show that the system operates with the accuracy is over 80% and could be implemented in practice.

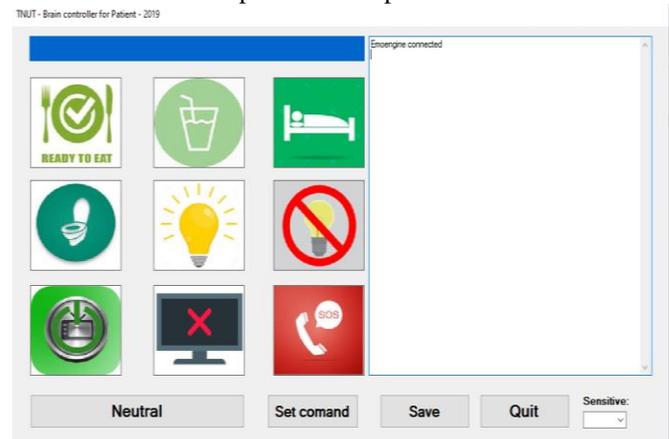


Fig 11. Training GUI

Table 2. Some test results

Command	Number of test sample	Number off Accuracy sample	Rate %
Eat	50	43	86
Drink	50	42	84
Sleep	50	43	86
WC	50	45	90
Turning on the lights	50	43	86
Turning off the lights	50	42	84
Turning on the TV	50	41	82
Turning off the TV	50	43	86
Relative calling	50	44	88
Neutral	50	46	92

The results show the high accuracy. However, this is only result for a same person. For the others, we have to sample and identify from beginning. This will impact the real system operation because it is very difficult for the patient to accurately implement training network. In the future, we will study a method to achieve the thought features which are common for all objects. Besides, in the testing process, system faces to difficulties caused by delays of control commands.

IV. CONCLUSIONS AND FUTURE WORK

Obviously, “automatically identify brainwave by machine” is a complex problem but we can solve them by applying some research results in the signal processing, mathematics, artificial intelligent, control systems fields.

In this paper, we present a methodology for design (both hardware and software) of patient support brainwave communication system. About hardware, system collect the brainwave data through Emotiv’ Epoc+ headset, send it to Pi3 microprocessor. The software is programmed to identify human thought and send the code command to the actuator. The system works with high accuracy and could be used for many other applications as smart house, wheelchair control system.

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Assoc. Prof. Thanh Ha Nguyen is PhD in Measurement and Control Engineering at Hanoi University of Technology, Vietnam. He is working at Thai Nguyen University, Thai Nguyen City, Vietnam. Research interests: Digital Signal Processing, Measurement and Control Engineering, Automation.



MSc Thi Mai Thuong Duong is working at Faculty of Information Technology, University of Information and Communication Technology, Thai Nguyen City, Vietnam. Research interests: Computer science.



Mr. Toan Luu Van is working at Department of Electrical – Electronics, Faculty of Mechanical Engineering – Motivation, Faculty of Information Technology, The North - eastern College of Technology, Agriculture and Forestry University, Lang Son, Vietnam. Research interests: Electronics Engineering, Automation.



Dr. Phuong Huy Nguyen is PhD in Telecommunication Engineering at Hanoi University of Technology, Vietnam. He is working at Faculty of Electronics Engineering, Thainguyn University of Technology, Thai Nguyen City, Vietnam. Research interests: Digital Signal Processing, Soft computing, Fuzzy control.