Developing a Wheelchair System Controlled Based on EEG Signal and Eye-Direction

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Summary
The electroencephalographic (EEG) signal recognition to support disabled people controlling electric wheelchair is being considered by many researchers. This paper proposes a novel solution for online recognition of EEG signals and eye-direction when users look at the different types of images. A hardware and software communications system based on the above mentioned solution is designed to experiment. With 80 students volunteering to participate in the experimental process, the experimental result show that the best recognition rate of the proposed solution is over 91%.

Key words:
EEG signal, Brain-computer interface (BCI), Neural Network, Clustering, Hilbert–Huang Transform (HHT)

1. Introduction

The electroencephalogram (EEG)-based brain-computer interfaces (BCI) [1] can provide a new way for the elderly and disabled people communicate with the outside world. The purpose of a BCI is to interpret user intentions to translate into control signals for output devices [2]. EEG signal analysis was applied in medicine such as early detection of Alzheimer [3], epilepsy [4] and applied in telecommunication such as calling or listening music based on EEG brain signal [5].

In these recent years, EEG signal recognition to support disabled people controlling electric wheelchair is being considered by many researchers. According to previous studies, EEG signals are recognized based on eye blink [6], eye movement [7] or head movement [8]. However, People with disabilities who are unable to move their heads, move their eyes or wink, the EEG signal cannot be recognized.

This paper proposes an EEG signal recognition model to control electric wheelchairs based on the EEG signal received when users look at the different types of images, and combine with eye-direction from the camera. This paper is improved from our previous work [9]. The contributions of this paper focus on the following sections:

- Using Hilbert–Huang Transform (HHT) for EEG signal denoising because HHT is suitable for EEG signals.
- Eye-direction recognition based on user's facial image combining with EEG signals recognition aim to improve the effectiveness of recognition.
- Design a system including hardware and software to experiment in the real world.
- Experimental data is collected from 80 students volunteering to participate in experiments.

The rest of the paper is structured as follows. The proposed method is described in detail of Section 2. Evaluation of the proposed method is presented in Section 3. Section 4 gives conclusions and outlines future research directions.

2. Proposed Method

The system architecture including 3 blocks is presented in Figure 1.

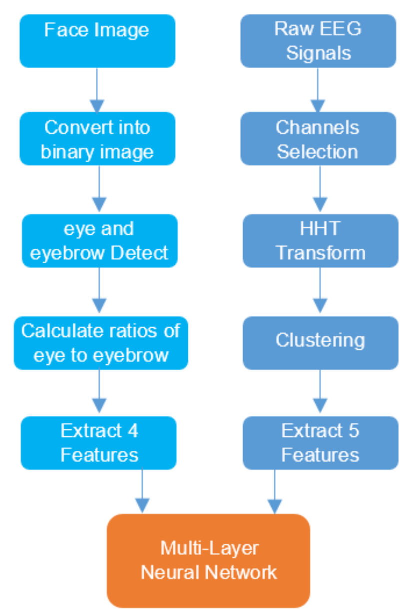

Fig. 1 Proposed System Architecture

- The first block is the "EEG Signal" block which recognizes EEG signals to extract 5 features, and these features are input nodes of neural network.
- The second block is the "Eye-Direction" block which recognizes eye and eyebrow from user's facial image to extract 4 features, and these

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features are input nodes of neural network.

- The third block is multi-layer neural network with 5 output nodes which classify into 5 control signals such as "go forward", "go backward", "turn left", "turn right" and "stop".

2.1 "EEG Signal" Block

This block is described in Figure 2.

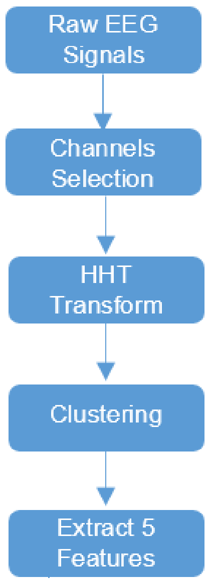

Fig. 2 EEG Signal Block

First, selecting 10 electrode locations commonly used such as F3, C3, P3, O1, F4, C4, P4, O2, A1 and A2, because many of the EEG channels appeared to represent redundant information [10]. Next, Hilbert-Huang transform (HHT) is a data-dependent and posteriori defined signal analysis algorithm. Comparing with other time frequency analysis methods, HHT has an adaptive ability to track the evolution of time-frequency basis in the original signal without employing a time or frequency resolution window, and also can provide much detailed information at discretionary time-frequency scales. Raw EEG signals suffer from poor spatial resolution, low signal-to-noise ratio and artifacts [11, 12, 13, 14]. Then, Clustering method divides a dataset into groups according to similarities or dissimilarities among the patterns. K-means algorithm is one of the simplest and well known clustering algorithms [15]. This algorithm determines the cluster centers and the elements belonging to them by minimizing the squared error based objective function. The aim of the algorithm is to locate the cluster centers as much as possible far away from each other and to associate each data point to the nearest cluster center [16]. Finally, K=5 is used to group into 5 clusters such as Delta, Theta, Alpha, Beta and Gamma.

2.2 Eye-Direction Block

This block is described in Figure 3.

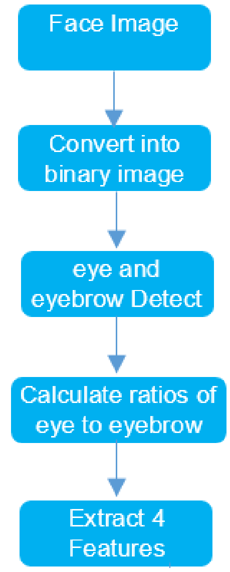

Fig. 3 Eye-Direction Block

This block performs step by step as follows:

- User's facial image is received from camera.
- Facial image is converted into binary image.
- Eyes and eyebrows are detected as shown in Figure 4. A threshold value is dynamically calculated using isodata algorithm [17].
- Using image segmentation algorithm to detect pupil center of eyes, segmentation of eyes and eyebrows as shown in Figure 5.
- Calculating ratio left eye and left eyebrow by equation (1) as shown in Figure 6.

$$d1 = l2/l1 \tag{1}$$

- Calculating ratio right eye and right eyebrow by equation (2) as shown in Figure 7.

$$d2 = r2/r1 \tag{2}$$

- Calculating ratio pupil center of left eye and length of left eye by equation (3) as shown in Figure 8.

$$d3 = l3/l4 \tag{3}$$

- Calculating ratio pupil center of right eye and length of right eye by equation (4) as shown in Figure 8.

$$d4 = r3/r4 \tag{4}$$

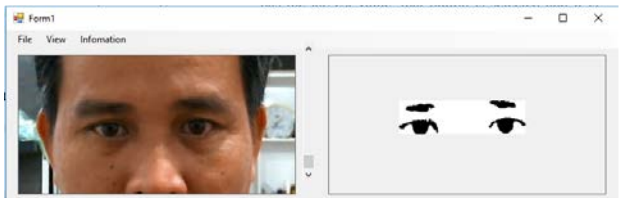

Fig. 4 Eyes and Eyebrows Detected

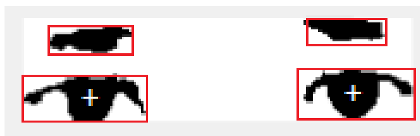

Fig. 5 Pupil Center of Eyes, Segmentation of Eyes and Eyebrows

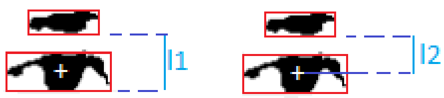

Fig. 6 Ratio Left Eye and Left Eyebrow

Fig. 7 Ratio Right Eye and Right Eyebrow

Fig. 8 Ratio Pupil Center of Eyes and Length of Eyes

2.3 Neural Network Block

Artificial neural network (ANN) has one input layer, one output layer and one or more hidden neuron layers. Theoretically network with one hidden layer of neurons can solve task of any complexity [18]. The proposed multi-layer neural network model including 3 layers is presented in Figure 9.

- The first layer contains 9 nodes such as delta, theta, alpha, beta, gamma, d1, d2, d3 and d4. This layer is called the input layer.
- The second layer is the hidden layer. According to [19], the number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer. So, the number of neurons in hidden layer is 11 neurons.
- The output layer contains 5 nodes, the results of this node are used to classify EEG signal. Due to the action function used in this model is hyperbolic tangent function, the value of the output node ranges in the interval [-1, 1]. Figure 10 shows the output result. Because the output has 5 output nodes, which node has the largest value, that node is selected and it is control signal.

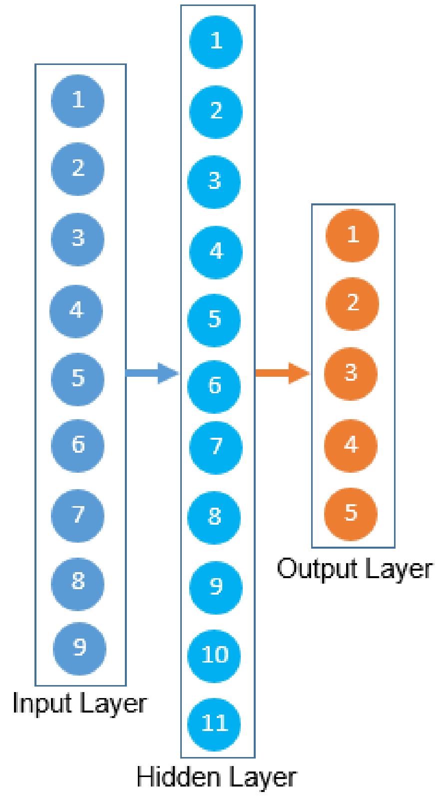

Fig. 9 Multi-Layer Neural Network

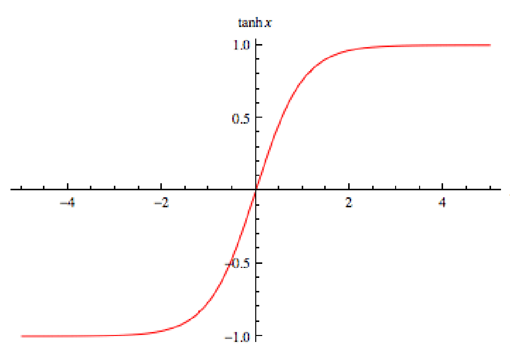

Fig. 10 Hyperbolic Tangent Function

3. Evaluation

To evaluate the proposed method, we design a hardware and software communications system. Then, we collect experimental data from 80 students participate in volunteering and carry out experiments. a hardware and software communications system is described in Figure 11.

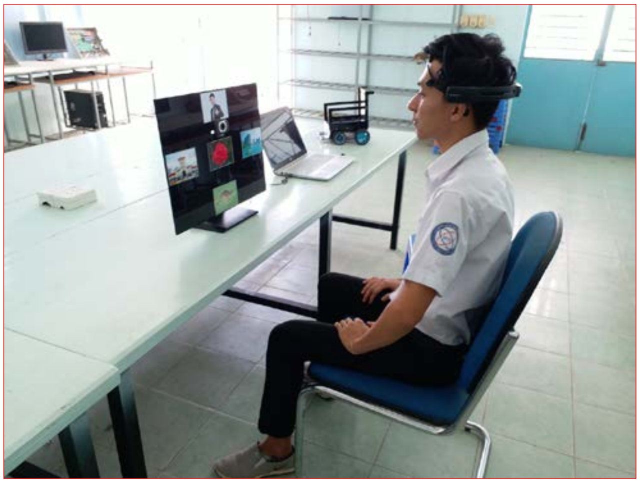

Fig. 11 Hardware and Software System

3.1 Hardware

The hardware of system includes the following components such as wheelchair, observation board and EEG headset.

3.1.1 Wheelchair

We design wheelchair described in Figure 12, the wheelchair communicates with the computer via Bluetooth.

Fig. 12 Wheelchair

3.1.2 Observation Board

Observation board is the board containing a camera and 5 images corresponding to control commands such as human image (Go Forward), animal image (Go Backward), city image (Turn Left), landscape image (Turn Right) and flower image (Stop). Observation board is described in Figure 13.

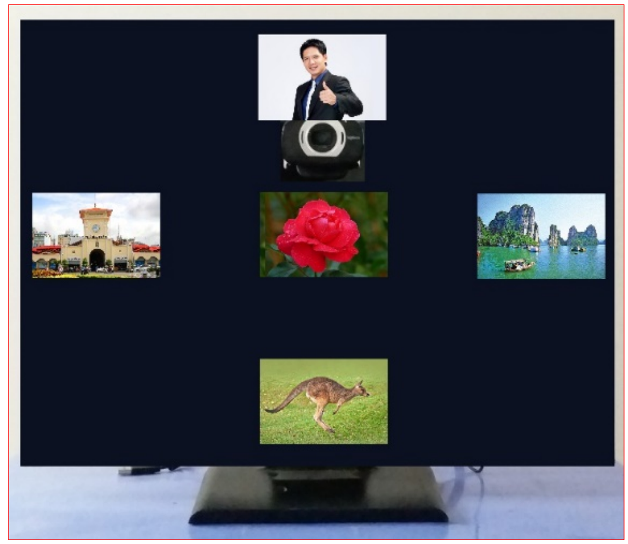

Fig. 13 Observation Board.

3.1.3 EEG Headset

The system uses Emotiv EEG headset described in Figure 14. This device was purchased from Emotiv company.

Fig. 14 Emotiv EEG Headset

3.2 Software

The software system is programmed in C # language on Visual Studio environment. The functions of the software system are as follows:

- Receiving EEG signals for processing and extracting 5 features such as delta, theta, alpha, beta, gamma.
- Recognizing eye and eyebrow from user's facial image for processing and extracting 4 features

such as d1, d2, d3, d4.

- Training and testing neural network.
- Collecting experimental data from users.
- Controlling wheelchair with control signal from the output result of neural network. Control signals from the output result of neural network are described in Figure 15, 16, 17, 18, 19.

Fig. 15 Control Signal “Go Forward”.

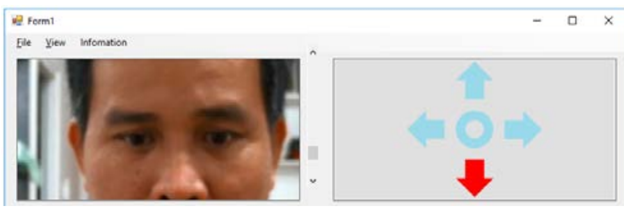

Fig. 16 Control Signal “Go Backward”.

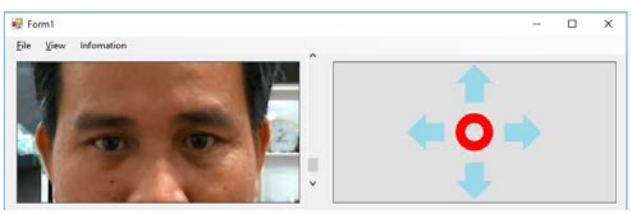

Fig. 17 Control Signal “Stop”.

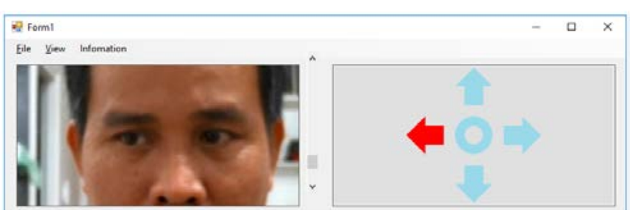

Fig. 18 Control Signal “Turn Left”.

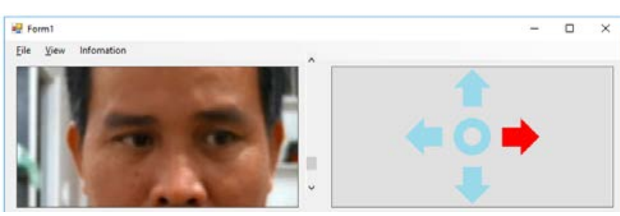

Fig. 19 Control Signal “Turn Right”.

3.3 Experimental Data

Experimental data was collected from 80 students participate in volunteering. Students wear Emotiv EEG headset and sit 120cm far from the observation board. Students perform the process as follows:

- When students hear “Go Forward”, students look up and look at “human image” on the observation board about 2 seconds.
- When students hear “Go Backward”, students look down and look at “animal image” on the observation board about 2 seconds.
- When students hear “Turn Left”, students look left and look at “city image” on the observation board about 2 seconds.
- When students hear “Turn Right”, students look right and look at “landscape” image on the observation board about 2 seconds.
- When students hear “Stop”, students look straight and look at “flower image” on the observation board about 2 seconds.

Each student performs the above process 10 times at different time.

3.4 Experimental Process

Experimental data was divided into 3 datasets as follows:

- The training dataset was gathered from 70% of data of 60 students.
- The first testing dataset was gathered from 30% of data of 60 students.
- The second testing dataset was gathered from the remaining 20 students.

Experimental process includes training phase and testing phase.

3.4.1 Training Phase

The neural network need to pass the training phase to learn. The flow of the training algorithm represents a back propagation learning procedure [20]. This phase uses the training dataset to train with adaptive learning rate [21]. The parameters in training phase were set as follows:

- Mean error threshold value: $1x10^{-5}$
- Number of Epochs: 10,000
- The weights: initialize weights random values from -0.5 to 0.5

3.4.2 Testing Phase

This phase uses weighting sets trained from training phase to evaluate the first testing dataset and the second testing dataset.

3.5 Experimental Result

3.5.1 The first testing dataset

After performing the testing phase with the first testing dataset, the data of the confusion matrix [22] evaluating the performance of system was depicted in Figure 20.

		Actual Class				
		Humans	Animals	Flowers	Cities	Landscapes
Predicted Class	Humans	91.2%	1.6%	3.1%	0.9%	2.7%
	Animals	1.9%	91.1%	1.2%	3.2%	2.0%
	Flowers	2.8%	2.5%	92.8%	1.7%	1.5%
	Cities	2.4%	2.1%	0.7%	92.1%	1.9%
	Landscapes	1.7%	2.7%	2.2%	2.1%	91.9%

Fig. 20 Illustration of Confusion Matrix for The Result of Classification.

The success rates obtained by the testing with the first testing dataset are given in Figure 21. The average accuracy recognition rate is 91.8%.

	TP	TN	FP	FN	AC	P
Humans	91.2%	91.3%	8.7%	8.8%	91.3%	91.3%
Animals	91.1%	91.1%	8.9%	8.9%	91.1%	91.1%
Flowers	92.8%	92.6%	7.4%	7.2%	92.7%	92.6%
Cities	92.1%	92.2%	7.8%	7.9%	92.2%	92.2%
Landscapes	91.9%	92.1%	7.9%	8.1%	92.0%	92.1%

Fig. 21 The Experimental Result of The First Testing Dataset.

Here, True positives (TP) refers to the positive tuples that were correctly labeled by the classifier. True negatives (TN) refers to the negative tuples that were correctly labeled by the classifier. False positives (FP) refers to the negative tuples that were incorrectly labeled as positive. False negatives (FN) refers to the positive tuples that were mislabeled as negative. The accuracy (AC) is the proportion of the total number of predictions that were correct. The precision (P) is the proportion of the predicted positive cases that were correct.

3.5.2 The second testing dataset

After performing the testing phase with the second testing dataset, the data of the confusion matrix [22] evaluating the performance of system was depicted in Figure 22.

		Actual Class				
		Humans	Animals	Flowers	Cities	Landscapes
Predicted Class	Humans	90.7%	1.9%	2.7%	1.1%	3.1%
	Animals	1.4%	90.8%	2.1%	2.6%	2.4%
	Flowers	2.3%	2.3%	92.3%	3.2%	1.7%
	Cities	3.1%	2.6%	1.2%	91.6%	1.3%
	Landscapes	2.5%	2.4%	1.7%	1.5%	91.5%

Fig. 22 Illustration of Confusion Matrix for The Result of Classification.

The success rates obtained by the testing with the second testing dataset are given in Figure 23. The average accuracy recognition rate is 91.5%.

	TP	TN	FP	FN	AC	P
Humans	90.7%	90.9%	9.1%	9.3%	90.8%	90.9%
Animals	90.8%	91.0%	9.0%	9.2%	90.9%	91.0%
Flowers	92.3%	92.1%	7.9%	7.7%	92.2%	92.1%
Cities	91.6%	91.8%	8.2%	8.4%	91.7%	91.8%
Landscapes	91.5%	91.9%	8.1%	8.5%	91.7%	91.9%

Fig. 23 The Experimental Result of The Second Testing Dataset.

3.5.3 Another Experiment

In this experiment, we built 2 training datasets, the first training dataset was gathered from the EEG signal data of 60 students, the second training dataset was gathered from the eye-direction data of 60 students. Two testing datasets were also built as follows: the first testing dataset was gathered from the EEG signal data of 20 students, the second training dataset was gathered from the eye-direction data of 20 students.

Neural network is divided into 2 neural networks as follows:

- The first neural network includes the input layer containing 5 input nodes (delta, theta, alpha, beta, gamma), the hidden layer containing 8 hidden nodes and the output layer containing 5 output nodes. This neural network used to train and test for EEG signal data (the first training dataset and the first testing dataset).
- The second neural network includes the input layer containing 4 input nodes (d1, d2, d3, d4), the hidden layer containing 8 hidden nodes and the output layer containing 5 output nodes. This neural network used to train and test for eye-direction data (the second training dataset and the second testing dataset).

After training the first neural network with the first training dataset and training the second neural network with the second training dataset, we use the first neural network to test the first testing dataset and use the second neural network to test the second testing dataset, the experimental result is shown in Figure 24, 25, 26. The average accuracy recognition rate of the first testing dataset is 90.7% and the average accuracy recognition rate of the second testing dataset is 84.8%.

	TP	TN	FP	FN	AC	P
Humans	90.2%	89.9%	10.1%	9.8%	90.1%	89.9%
Animals	90.3%	90.0%	10.0%	9.7%	90.2%	90.0%
Flowers	92.3%	91.8%	8.2%	7.7%	92.1%	91.8%
Cities	90.7%	90.4%	9.6%	9.3%	90.6%	90.4%
Landscapes	90.4%	90.5%	9.5%	9.6%	90.5%	90.5%

Fig. 24 The Experimental Result of The First Testing Dataset.

	TP	TN	FP	FN	AC	P
Humans	85.1%	85.7%	14.3%	14.9%	85.4%	85.6%
Animals	84.5%	84.1%	15.9%	15.5%	84.3%	84.2%
Flowers	87.3%	86.3%	13.7%	12.7%	86.8%	86.4%
Cities	83.6%	84.0%	16.0%	16.4%	83.8%	83.9%
Landscapes	84.2%	83.2%	16.8%	15.8%	83.7%	83.4%

Fig. 25 The Experimental Result of The Second Testing Dataset.

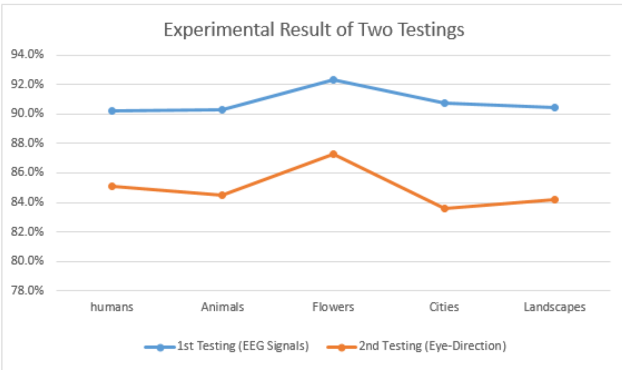

Fig. 26 Experimental Result of Two Testings

3.6 Discussion

From the experimental result of section 3.5.1 and 3.5.2, we found that the successful recognition rate of the first testing dataset is better than the successful recognition rate of the second testing dataset because the first testing dataset and the training dataset are collected from students in the same group (60 students), but the second testing dataset and the training dataset are collected from two different student groups (60 students and 20 students).
The experimental result of section 3.5.3 shows that recognizing EEG signals and eye-direction separately is not as good as combining EEG signals with eye-direction. If only eye-direction is recognized, the result is quite low (84.8%). Therefore, recognizing EEG signals and eye-direction will achieve better results.
These results are also compared to some previous studies such as the technique [6] identify EEG signals based on blink with 15,360 samples and reach 90.85%, the technique [7] with the decision tree achieving a maximum of 85% , the technique [8] based on eye movement by 2 experiments with 3,600 samples and 8,320 samples and reach 85%. We found that the proposed method gives better results. However, the proposed method is not as good as our previous work [9] because of the following reasons:

- Experimental data of the proposed method is not big enough. But, experimental data of our previous work [9] is very big.
- Experimental data is gathered online so there is a lot of noise and pre-processing is not as good as data in our previous work [9].
- Some students did not perform well in the experimental process.
- The quality of the camera is not very good.

4. Conclusion

This paper proposed a novel approach to classify control signals based on EEG signals and eye-direction by a hardware and software system. The proposed method was experimented with 80 students participate in volunteering. The experimental results show that the proposed method achieved good results. However, the achieving results are not the best. Thus, in the future, our group will improve the system aim to get more and more better results such as collecting experimental data bigger, data noise reduction better, adjusting the parameters of the neural network to achieve optimal performance, etc.

Acknowledgments

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References

[1] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks et al., "Brain-computer interface technology: a review of the first interna-tional meeting,"IEEE Transactions on Rehabilitation Engineer-ing, vol.8,no.2,pp.164–173, 2000.
[2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," Clin. Neurophysiol. , vol. 113, pp. 767–791, 2002.
[3] Hornero et al., 2009. Nonlinear analysis of electroencephalogram and magnetoencephalogram recordings in patients with Alzheimer's disease. Phil. Trans. R. Soc. A 367:317–336.
[4] Smith S J M. EEG in the diagnosis, classification, and management of patients with epilepsy. Journal of Neurol Neurosurg and Psychiatry 2005;76:ii2-ii7.
[5] Demo-Video. Neurophone (September, 2017). http://www.youtube.com/watch?v=tc82Z_yfEwc.
[6] Brijil Chambayil, Rajesh Singla, R. Jha, "EEG Eye Blink Classification Using Neural Network", pp 603-608, vol 1, Springer-Verlag Berlin Heidelberg, July 2, 2010.
[7] Chadwick, N.A.; McMeekin, D.A.; Tan, T., Classifying eye and head movement artifacts in EEG signals, Proceedings of the 5th IEEE International Conference on Digital Ecosystems and Technologies Conference (DEST), pp. 285 – 291, 2011.
[8] Abdelkader Nasreddine Belkacem, Hideaki Hirose, Natsue Yoshimura, Duk Shin,Yasuharu Koike, Classification of Four Eye Directions from EEG Signals for Eye-Movement-Based Communication Systems, Journal of Medical and Biological Engineering, 34(6): 581-58, December 2014.
[9] Quang Chuyen Lam, Luong Anh Tuan Nguyen, and Huu Khuong Nguyen " Build Control Command Set Based on EEG Signals via Clustering Algorithm and Multi-Layer

Neural Network," Journal of Communications, vol. 13, no. 7, pp. 406-411, 2018. Doi: 10.12720/jcm.13.7.406-411.
[10] Chi-Chun Lo, Tsung-Yi Chien, Yu-Chun Chen, Shang-Ho Tsai, Wai-Chi Fang, and Bor-Shyh Lin, “A Wearable Channel Selection-Based Brain-Computer Interface for Motor Imagery Detection,” Sensors, vol. 16, no. 2, 2016.
[11] Huang NE. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc Math Phy Eng Sci 1998; 454: 903-995.
[12] Temko A, Boylan G, Marnane W, Lightbody G. Robust neonatal EEG seizure detection through adaptive background modeling. Int J Neural Syst 2013;23(4): 1350018.
[13] Liu, Z & Ying, Q & Luo, Z & Fan, Y. (2016). Analysis and research on EEG signals based on HHT algorithm. 423-426. 10.1201/9781315265278-95.
[14] Köse, Ayşe & Sarabaty, H. (2017). EEG Signals Analysis using Hilbert-Huang Transform.
[15] Alexander J. Casson, David C. Yates, Shyam Patel and Esther Rodriguez-Villegas, An analogue bandpass filter realisation of the Continuous Wavelet Transform, Proceedings of the 29th Annual International Conference of the IEEE EMBS, pp. 1850-1854 Lyon, France August, 2007.
[16] Mwasiagi, J. I., Wang, X. H., & Huang, X. B. (2009). The use of K-means and artificial neural network to classify cotton lint. Fiber and Polymers, 10, 379–383.
[17] T. W. Ridler and S. Calvard, “Picture thresholding using an iterative selection method,” IEEE Transactions on Systems, Man and Cybernetics, SMC-8, pp.630-632, 1978.
[18] S. O. Haykin, “Neural networks and learning machines,” Prentice Hall, 2008.
[19] Heaton, Jeffrey. (2008). Introduction to Neural Networks for Java.
[20] Jiawei Han, Micheline Kamber, Data Mining: Concepts and Techniques, Second Edition, Elsevier Inc. All rights reserved, 2006.
[21] Z. X. Bo and W. L. Li, "Handwritten digit recognition based on improced leaning rate BP algorithm," in Proc. 2nd International Conference on Information Engineering and Computer Science, pp. 1-4, 2010.
[22] Kohavi, R. and F. Provost (1998). Glossary of terms . Editorial for the Special Issue on Applications of Machine Learning and the Knowledge Discovery Process.

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