USING EEG BRAINWAVES AND DEEP LEARNING METHOD FOR LEARNING STATUS CLASSIFICATION

CHUNG-YEN LIAO, RUNG-CHING CHEN*

Department of Information Management Chaoyang University of Technology, Taichung, Taiwan
E-MAIL: s10514901@gm.cyut.edu.tw, *crching@cyut.edu.tw

Abstract:

This study is conducted specifically to measure human's brain waves; the evaluation is built based on the energy of watching a video. Brainwave reflects the change in electrical potential resulting from the conjunction between the thousands of brain neurons. A neuron can receive signals from other neurons and starts off cyclic discharge reaction when sufficient energy is accumulated. That is also the reason why people persistently emit brainwaves. However, for some people rely on their brain to deal with many things and it may lead to learning status. The learning status includes good, questionable and bad. In this paper, we aim to classify their learning status by conducting choices in the system to be chosen when users watching to the video. Users need to click choices in the system. Then, using deep learning to predict their learning status through the experiments. The experimental results indicated this method is valuable for learning status predication.

Keywords:

Deep learning; Fast fourier transform; EEG signal; Learning status classification.

1. Introduction

In different sensory states, healthy people show different frequencies of brainwaves. These rhythmic brainwaves are often influenced by actions and thoughts and have specific reactivity [1]. The EEG is [2] [3] the most commonly used fundamental wave to describe the brain frequency band division and the different types of brainwaves that reflect brain mental states. According to the technical documents provided by NeuroSky [4] and according to the International Federation of Clinical Physiology for Clinical Neurophysiology [5] and other information, brainwaves are issued by the physiological signal. FIGURE 1 is the Alpha, Beta, Theta, Delta, and Gamma waveform legend [6].

Based on the frequency range, brainwaves are classified into five categories: 1). Delta activity (δ wave): The frequency is below the 3 Hz and its amplitude is about 20-200μV. Delta wave usually occurs when sleeping and not awake, or under deep anesthesia or hypoxia, or with brain lesions in patients. 2). Theta activity (θ wave): The frequency is between 4 Hz and 7 Hz. In general, it presents a smaller amplitude. Theta wave mainly occurs in child's top lobe and temporal lobe. When adults are under emotional pressure, a small number of Theta waves will appear. However, there is no regular type, and they may occur in a sleepy or highly relaxed state. This band is very important to be analyzed because of many other brain disease patient exhibit θ waves.

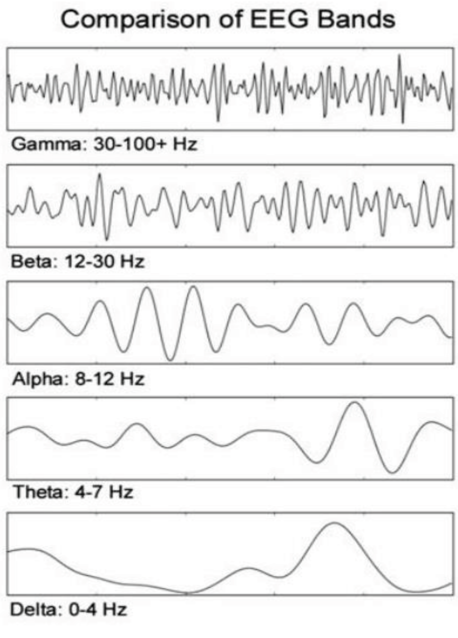

FIGURE 1. Comparison of EEG Bands [6].

3). Alpha activity (α wave): The frequency is 8-13 Hz, and the amplitude is about 20-200μV. For most people, the brain Alpha wave is generated in the sober, quiet and relaxed state. To improve Alpha wave activities, people need to close their eyes and feel relax. 4). Beta activity (β wave):

978-1-5386-5214-5/18/$31.00 ©2018 IEEE

The frequency is 13 Hz or more, but rarely higher than 50 Hz. Studies have shown that Beta waves are influenced by tactile, auditory, and emotional stimuli and controlled by self-effort. 5).Gamma activity (γ wave): The frequency is between 31 and 50 Hz. In recent years, researchers have found that this wave is related to user's attention, raising awareness, happiness, and reducing stress. The meditation has a connection with human cognition and perceptual activity which related to gamma wave [7] [8].

Our contributions are that we propose a novel method to predict confusedness level of the users from watching video utilizing deep learning and EEG brainwaves signals. We propose to classify confusedness level into three categories such as Good, Questioning and Bad, and then develop a model to predict this classification category from users EEG brainwaves signal.

The remainders of the paper are organized as follows. Section 2 is system's research instruments. Section 3 is deep learning algorithm to predict confusedness level from EEG brainwaves signal. Section 4 is the discussion of the results of experiments to show the performance of deep learning training model. Finally, we give conclusions and future work in Section 5.

2. Research Instrument

The system's instruments consist of Hardware and Software which are used in this experiments as follows:

1. Hardware: Mindwave Mobile, Asus Notebook (Intel Core i5-6200U, DDR4 4GB, Geforce 930MX, Windows 10), Bluetooth 3.0 transmitter.
2. Software device: Microsoft Visual Studio 2017, Excel 2016, IBM SPSS Statistics v22, Microsoft Visual C # 7.0.

Mindwave Mobile Mindwave Idea Headset is a non-invasive, dry electrode technology developed by NeuroSky Corporation of the United States for brainwave detection equipment, as shown in FIGURE 2.

This brainwave instrument can accurately detect the focus and relaxation of the human body with high accuracy. The accuracy is 96% similarity compared with the device which medical grade Neuroscan brainwave instrument had that worth $40,000 [9]. FIGURE 3 shows comparison results of brainwave measurement between MindWaveMobile and Neuroscan brainwave devices.

The device can measure the pattern and frequency of the bioelectrical signals emitted by the neurons of the brain by the sensor placed on the scalp. The position of the sensor is based on the Fp1 of the international 10-20 system proposed by Jasper [5] in 1958 Position, and the reference point is at A1 as shown in FIGURE 4.

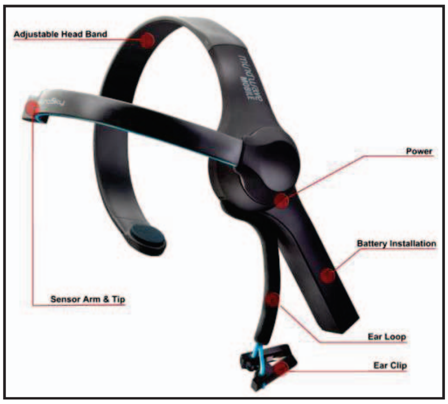

FIGURE 2. Mindwve Mobile Brainwave Device.

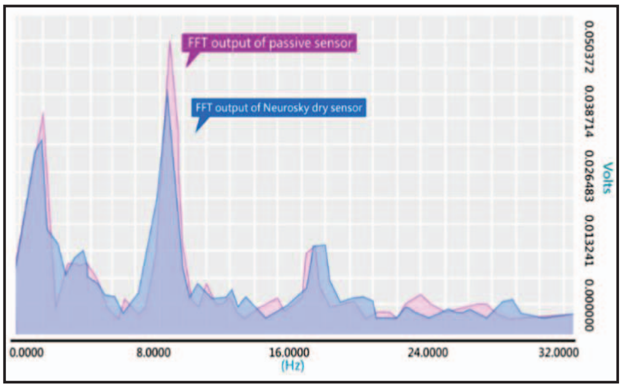

FIGURE 3. Comparison results of brainwave measurement between Mindwave Mobile and Neuroscan brainwave devices [9].

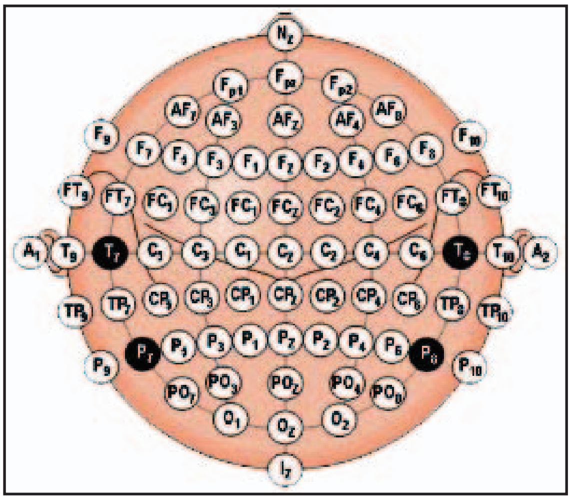

FIGURE 4. International brainwave electrode configuration method [5].

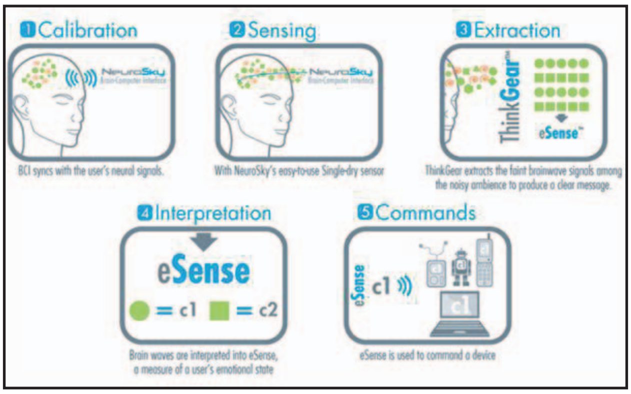

FIGURE 5. Ideas headset implementation process [10].

Using the dry electrode sensor to collect the biological signals generated by the brain could be collected into the ThinkGear™ chip [10]. ThinkGear™ chip technology is the original brainwave signal acquisition, filtering, amplification, A/D conversion, filtering environment, noise, and muscle movement of the interference, data processing, and analysis functions are fully integrated into an ASIC chip. Through the computer brainwave data is processed to digital output, showing the current state of mind to measure the algorithm, after the calculation can be quantized parameter values are shown in FIGURE 5. From FIGURE 5 we could find the explanation as follows:

1. Signal calibration: the brainwaves of different users to calculate and synchronize the output, in order to achieve the accuracy of the signal.
2. Signal acquisition: the use of NeuroSky single-guided dry electrode technology, making the EEG signal acquisition becomes simple and easy to use.
3. Signal Extraction: ThinkGear™ separates the brainwave signal from the noisy environment, which is amplified to produce a clear brainwave signal.
4. Information Interpretation: The eSense™ patent algorithm interprets brainwaves as eSense ™ parameters, indicating the current mental state of the user.
5. Human-computer interaction: the eSense™ parameters passed to the computer, mobile phones, and other intelligent devices, and then through the brainwaves for human-computer interaction.

Through the NeuroSky ThinkGear technology to collect brain analog signals, that is, we usually referred to brainwaves, and then analog signals into digital signals, with Bluetooth transmission, so that a variety of applications can use these signals for interactive control this set of brainwave measurement. The system has been studied and applied in various fields, such as athlete research (Diefenbach, Bhatt, et al. 2004) [11], and to establish its convenience, comfort, and availability (Rebolledo-Mendez, Dunwell, et al. 2009) [10]. NeuroSky can measure each brainwave segment per millisecond 7 data, can be measured in the brainwave segment 0Hz ~ 63Hz, covering all the brainwaves and can be measured by the attention and emotions. The two physiological values of the Meditation are combined with the program [12] [13]. Brain cube mobile's version of the relevant specifications as shown in TABLE 1 and TABLE 2.

To ensure the reliability and reliability of NeuroSky's brain movement, the use of the "Birdwatching" training game developed by Lumosity, an online brain forging company in the United States, was used as a test of the reliability standard. The results showed that NeuroSky's brain movement version of brainwaves thinking headphones based on the value of the brainwaves measured by a certain degree of reliability and validity, so we think that the brain side of the mobile version of brain thinking headphones can be used as the research tool.

TABLE 1. Brain cube mobile version Bluetooth specification

Bluetooth	
Version	3.0
Output Power	Class 2
Minimum output voltage	1.0 V
Range	10 m
Consumption power ratio	80mA(Connection and transmission status)
Low battery power indication	1.1 V
UART (String type)	VCC, GNC, TX, RX
UART Baud rate	57,600 bps

TABLE 2. Brain cube mobile version EEG and signal specification

Signal and EEG signals	
EEG maximum signal input range	1mV pk-pk
Hardware filtering	3Hz – 100 Hz
Amplify gain	2000x
ADC Resolution	12bits
Sampling rate	512Hz
eSense Resolution rate	1Hz

3. Research Methods

In this section, we will present our research methodology by utilizing deep learning and EEG brainwaves signal.

3.1. System Architecture

System objectives want to achieve the following six points:

1). We develop Multi-person real-time connection EEG analysis design that can carry more than one person while operating the system.

2). Develop Brainwave signal cloud statistics processing module, so the user feedback records and brainwave values could be transmitted to the backend server.

3). Develop multimedia audio and video transmission integration with brain-machine interface window, so the system and the connection of brainwave instrument could be connected.

4). Develop real-time opinion feedback analysis of brainwave and feedback the information with the evaluation of the content from the users.

5). Construct cloud service procedures and decentralized computing, the brainwave sensor data, statistical data, and statistical model are presented in the system.

6). Capture brainwave raw data instantly upload to the cloud database, it instantly transmitting the operator's brainwave value to the cloud server.

FIGURE 6 shows our system architecture. The first step of our system is to calibrate our devices with the tests subjects in order to achieve the stability of their brainwaves data. After our devices are calibrated, we let the users watch movie[i] for ten minutes and capture their brainwaves. When the users are watching movie, they also could do interactive to press a button on the system while watching a movie which is contained by the question.

After we collect the EEG brainwaves data to the dataset, we utilized FFT (Fast Fourier Transform) to get their frequency bands from EEG raw data as shown by Equation 1.

$$x(t) = \frac{a_0}{2} + \sum_{k=1}^{\infty}(a_n \cos(\omega k t) + b_n \sin(\omega k t)) \quad (1)$$

where signal *x(t)* is integration able on an interval [*0, T*] and is periodic with period *T*, *t* is a time variable, ω is an angular frequency and a_0, a_n, b_n are Fourier coefficients.

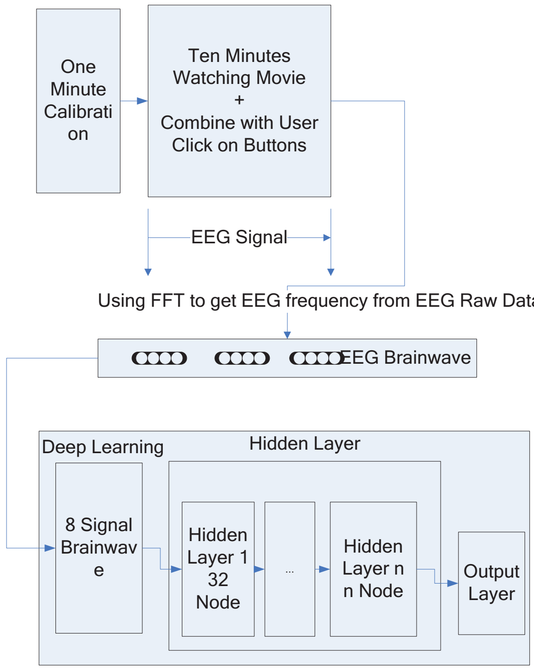

FIGURE 6. The System Architecture.

3.2. Deep Learning Architecture

For the deep learning, the system implements a deep back-propagation network to predict the mental state of the users from EEG signal data.

$$H_h = f(net_h) = \frac{1}{1+e^{-net_k}} \quad (2)$$

$$net_h = \sum_i W_{ih} \,.X_i - \theta_h \quad (3)$$

Back-propagation neural network has been widely used in machine learning research topics. The back-propagation network consists of the input layer (*X*), hidden layer (*H*) and an output layer (*Y*). Equation 3 is the computation of neural network between input and hidden layer. For every node in *X* which are connected to every node in H are calculated by Equation 2. Equation 2 calculates the sum of net_h for each node in the hidden layer. Theta is the bias of every node in the hidden layer. The process will be continuous until finish condition is reached.

$$Y_j = f(net_h) = \frac{1}{1+e^{-net_j}} \quad (4)$$

$$net_j = \sum_i W_{hj} \,.H_h - \theta_j \quad (5)$$

Equation 4 is the computation neural network of output layer and hidden layer. The process is similar to the computation of input and hidden layer. Every node in the hidden layer will be computed by Equation 5 and this process also repeated until the satisfying condition is reached.

4. Experiments and Results

In the experiments, we collect data from participants who are students from cram school. There are seven users in the experiment. They are three females and four males whose average age was 23.6 years old.

FIGURE 7 shows each brainwaves data from user1, which are generated automatically using FFT from raw brainwaves data. We could automatically collect their brainwaves frequency. Our dataset is label data, with three class labels are Good, Question and Bad. Now using these brainwaves frequency as input layer into deep learning training model. The system aims to predict the classification of the brainwaves into class labels.

Our deep learning model is consist of 7 hidden layers, with each layer contains nodes respectively 32,32,16,16,8,8 and our output layer consists of three nodes as our class labels. We use ReLU activation function with dropout and regularization. Our dropout rate is 0.4 and regularization learning rate is 0.00001 and weight decay is 0.000001.

FIGURE 8 shows our deep learning training model. The system gain convergences after 64 iterations with 0.6251 accuracies.

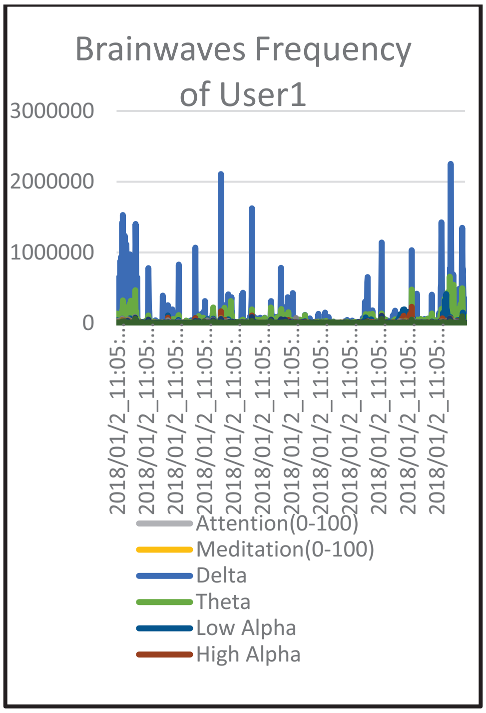

FIGURE 7. Raw EEG Brainwaves Data from User1

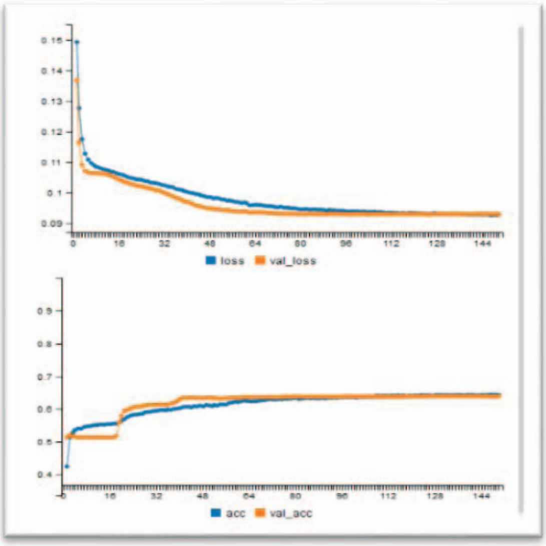

FIGURE 8. Deep Learning Loss and Accuracy

5. Conclusions

We propose confusedness level classification utilizing deep learning and brainwaves EEG frequency. Our system achieves convergences after 64 iterations with accuracy 62.41% to predict whether users will feel Good, Questionable or Bad when they watching a movie of language school. In the near future, we will add external factors such as emotions, environments factors (humidity, temperature and noisy) as consideration to calculate the learning status levels.

Acknowledgements

This paper is supported by Ministry of Science and Technology, Taiwan, with project number: MOST-106-2221-E-324-025 and MOST-106-2218-E-324.

References

[1] U. Frith, Neuroscience: implications for education and lifelong learning, The Royal Society, 2011.

[2] S. Sun, "Ensemble Learning Methods for Classifying EEG Signals," in *International Workshop on Multiple Classifier Systems*, Prague, Czech Republic, 2007.

[3] S.-K. Tai, C.-Y. Liao and R.-C. Chen, "Exploration of Multi-Brainwave System Mainframe Design," *ICIC Express Letters, Part B: Applications,* vol. 8, no. 9, pp. 1307-1314, 2017.

[4] J. Katona, I. Farkas, T. Ujbanyi, P. Dukan and A. Kovari, "Evaluation of the NeuroSky MindFlex EEG headset brain waves data," in *Applied Machine Intelligence and Informatics (SAMI), 2014 IEEE 12th International Symposium on*, Herl'any, Slovakia, 2014.

[5] G. Klem, H. Lüders, H. Jasper and C. Elger, "The ten-twenty electrode system of the International Federation. The International Federation of Clinical Neurophysiology," *Electroencephalography and clinical neurophysiology. Supplement,* vol. 52, pp. 3-6, 1999.

[6] H. Gastaut, "Clinical and electroencephalographical classification of epileptic seizures," *Epilepsia,* vol. 10, pp. 2-13, 1969.

[7] CatherineTallon-Baudry and OlivierBertrand, "Oscillatory gamma activity in humans and its role in object representation," *Trends in Cognitive Sciences,* vol. 3, no. 4, pp. 151-162, 1999.

[8] J. Fell, G. Fernández, P. Klaver, C. E. Elger and P. Fries, "Is synchronized neuronal gamma activity relevant for selective attention?," *Brain Research Reviews,* vol. 42, no. 3, pp. 265-272, 2003.

[9] D. V. Poltavski, "The use of single-electrode wireless EEG in biobehavioral investigations," *Methods in Molecular Biology,* vol. 1256, pp. 375-390, 2015.

[10] G. U. Navalyal and R. D. Gavas, "A dynamic attention assessment and enhancement tool using computer graphics," *Human-centric Computing and Information Sciences,* vol. 4, no. 1, pp. 1-7, 2014.

[11] H. P. B. Diefenbach, A. Gupta, J. Lorenz, P. Lyon, C. Stevenson and P. Stratton, "Maxwell 's Demon: A Study in Brain-Computer Interface Game Development," [Online]. Available: http://www.mysorethumbs.com/docs/MD_ACMSubmission.pdf. [Accessed 5 March 2018].

[12] D. M. Taylor, S. I. H. Tillery and A. B. Schwartz, "Direct Cortical Control of 3D Neuroprosthetic Devices," *Science,* vol. 296, no. 5574, pp. 1829-1832, 2002.

[13] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn and J. P. Donoghue, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature,* vol. 442, pp. 164-171, 2006.

[i] https://www.youtube.com/watch?v=zdWAXEwfuHI