DE GRUYTER
Carpathian Journal of Electronic and Computer Engineering 11/2 (2018) 29-34
DOI: 10.2478/cjece-2018-0015

Processing EEG signals acquired from a consumer grade BCI device

Fanny Monori
Faculty of Informatics
University of Debrecen
Debrecen, Hungary
fannymonori@gmail.com

Stefan Oniga
Faculty of Informatics
University of Debrecen
Debrecen, Hungary
oniga.istvan@inf.unideb.hu

***Abstract*—BCI (Brain-Computer Interface) is a technology which goal is to create and manage a connection between the human brain and a computer with the help of EEG signals. In the last decade consumer-grade BCI devices became available thus giving opportunity to develop BCI applications outside of clinical settings. In this paper we use a device called NeuroSky MindWave Mobile. We investigate what type of information can be deducted from the data acquired from this device, and we evaluate whether it can help us in BCI applications. Our methods of processing the data involves feature extraction methods, and neural networks. Specifically, we make experiments with finding patterns in the data by binary and multiclass classification. With these methods we could detect sharp changes in the signal such as blinking patterns, but we could not extract more complex information successfully.**

Keywords— BCI, EEG, neural networks, MindWave Mobile

I. Introduction

EEG (electroencephalography) is a type of monitoring method that measures the electromagnetic change in the brain. The measurement is usually done with electrodes attached to the scalp, in a non-invasive way. In medical application the so called wet electrodes are used, to decrease the noise that the electrodes get from the environment as much as possible. In the last decade consumer grade devices became available, and they usually use dry electrodes instead of wet. It makes them easier to use but it also introduces more noise to the signal.

The BCI (Brain-Computer Interface) is a technology which goal is to create and manage a connection between the human brain and a computer. Since the birth of this discipline numerous applications have been created, in a wide variety of fields. Medical and rehabilitation fields are amongst the most populous fields in terms of patents and publications. Specifically, BCI applications can offer great help for people with disabilities. BCI can be used as a way of controlling wheelchairs [1], [2], or virtual keyboards for example [3]. Controlling prosthesis is also a widely researched area of the BCI discipline. There exists both invasive [4] and non-invasive [5], [6] methods. The latter many times utilizes the EEG patterns created when imagining left or right-hand movements [7], [8], [9]. Medical applications are not the only type of BCI applications. One popular field of BCI is helping car controlling. For example, J. Kim et al. [10] tried to derive from the EEG signals the exact moment where the driver started to initiate a brake. Alerting systems that watches the drowsiness of the driver is also a notable field in this field [11], [12].

These experiments were performed using clinical grade EEG devices, but in the last few years consumer grade BCI devices have appeared for the public. These devices usually take the form of some headset, and they usually have the means of not just processing the data but to send it over some forms of communication channels. These consumer grade devices without exception use dry electrodes, so they could be easily used at home. One of the most widely known producer is NeuroSky. The company has been producing their one-channeled devices since 2011 under the name of MindWave which comes with their EEG processing sensor, the ThinkGear ASIC Modul (TGAM). OpenBCI also produces consumer grade devices. They offer a variety of pre-assembled headsets, but they also offer the 3D design of their headset free charge. So, one can download the design, print it with the help of a 3D printer, and assemble it with a purchased OpenBCI sensor. Their devices utilize 16 to 35 channels. Emotiv also offers multiple of headsets. They have devices that have fewer electrodes (5) as well as more robust devices that can have up to 32 electrodes. Clinical grade BCI devices are also available for purchase. NeuroStyle for example is one of those companies that offer clinical grade products. Besides the EEG device, they also offer softwares for stroke-rehabilitation.

Many of the consumer graded devices were created with the intent of using them with games, but there exist examples of using them in scientific experiments. K. George et al. [13] used the Emotiv Epov headset in a seemingly simple experiment. They recorded EEG data with the headset while the wearer was looking at white and black squares on a monitor, and they developed a method for classifying these records. A. Kline et al. [14] also used Emotiv headset in their experiments. They tried to use the data provided by the headset for controlling prosthesis. N. Chumerin et al. [15] developed a game that can be controlled with human brain, and they used that as the basis of comparison between clinical and consumer grade BCI devices. C. Lin et al. [16] used one of NeuroSky's devices in an embedded system application that monitors the alertness of drivers. C. A. Lim et al. [17] and J. He et al. [18] developed methods for this problem also with the use of NeuroSky MindWave device.

We used a NeuroSky MindWave Mobile device, and in this paper, we investigate what kind of information can be obtained from a consumer grade device like this and whether it can be used in BCI applications. In Section II. we describe the usual process of evaluating EEG signals. In Section III. we describe the data types of MindWave Mobile. Then, in Section IV. we demonstrate our method of processing data values that were computed by the device itself. Finally, in Section V. we describe how we processed the raw data.

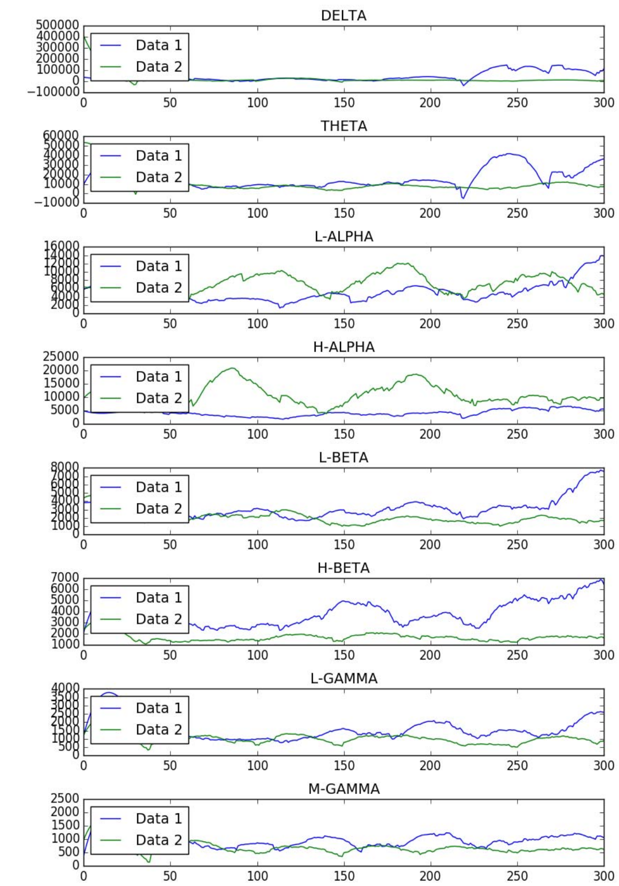

Fig. 1. Examples of EEG power values. Horizontal-axis represents time, and vertical axis represents the EEG Power values.

II. PROCESSING EEG SIGNALS IN GENERAL

Our brainwaves change according to our state and our environment. Low frequency brainwaves are often associated with relaxed state while higher frequency waves are associated with movements, and alertness.

Delta waves are at the lower end of the spectrum, their frequency is between the of 0.5 and 3 Hz. They are associated with deep, dreamless sleep. Theta waves are predominantly intense in the frontal region of the brain [19]. It is usually considered between the frequencies of 4-7 Hz. It is dominant in EEG records of wake children and sleeping adults. The alpha wave can be recorded more successfully in the posterior regions of the brain [20]. They are associated with relaxed, but alert state, for example being awake with closed eyes. The beta waves are associated with awake and alert state [21]. It is considered to be the basic rhythm of the awake adult brain. In the high-frequency end there lies the gamma rhythm which is associated with specific cognitive and motor functions. It should be noted that underlying diseases can influence the EEG patterns, for example slow wave activities in alert adults can suggest cerebral dysfunctions [19], [22]. But the normal EEG pattern of a person varies from task to task, and with a good EEG measurement device we can even associate a task to a given EEG pattern. We tried to investigate whether these normal states and the changes they go through in respect of time is observable in the acquired data.

This work was supported by the construction EFOP-3.6.3-VEKOP-16-2017-00002. The project was supported by the European Union, co-financed by the European Social Fund.

III. MINDWAVE MOBILE

A. *The device*

The NeuroSky MindWave Mobile is a type of consumer grade EEG headset that allows the user to record EEG data at home with the help of a one-channeled dry electrode. It transfers the data via Bluetooth which can be processed later with arbitrary devices as the communication protocol is available at NeuroSky's site.

This device includes one EEG recording electrode that lies on the front of the forehead, one clip that is attached to one of the earlobes, and the ThinkGear ASIC Module (TGAM). The electrode on the forehead records the activity of the frontal lobe. The electrode on the clip takes on the task of being the ground and reference. While usage the electrode on the forehead takes up not just the activity of the brain but also noise from the environment. So, the TGAM does a de-noising with the help of the ear clip's electrode before sending the data on Bluetooth. The TGAM has a sampling frequency of 512 Hz which then becomes the raw data, and it also does specific computations every one second.

B. *Types of data and the communication protocol*

The device can send the 16-bit raw data (sampled on 512 Hz) via Bluetooth and serial port at 57600 baud. The MindWave also sends computed values every one second. These values include controlling packets, like packets that indicate poor signal. It also sends valuable information like Attention and Meditation levels. The first one (a value between 0 and 100) indicates the alertness and the measure of concentration of the wearer [23]. The latter (also between 0 and 100) represents the calmness or relaxedness of the user [24]. The device also sends 8 values every second that represents the magnitude of 8 EEG wave patterns.

IV. PROCESSING THE PRE-COMPUTED SIGNALS

A. *EEG Power values*

These 8 values represent the following EEG wave patterns. Delta (0.5 – 2.75 Hz), theta (3.5 – 6.75 Hz), low-alpha (7.5 – 9.25 Hz), high-alpha (10 – 11.75 Hz), low-beta (13 – 16.75 Hz), high-beta (18 – 29.75 Hz), low-gamma (31 – 39.75 Hz), and high-gamma (41 – 49.75 Hz) [25]. These values are the results of various calculations thus they are only comparable with each other in respect of time, and they cannot be compared directly with magnitudes obtained from other type of devices [26].

We tried to find out whether changes in the activity of the subjects shows as changes in the signals. We recorded data in the following manner. We recorded data in a relaxed state while having our eyes closed. We also recorded data in a more alert state, with open eyes, while sitting in front of a computer and reading some text (which in theory is more of a concentration demanding task). 300 seconds of recordings are plotted in Fig. 1. where the first plot (named *Data 1*) belongs to the relaxed state and the second one (named *Data 2*) belongs to the mindful, alert state.

One can observe that there is a conspicuous difference between opened and closed eyed states. The alpha waves are stronger while having closed eyes, which is aligned to what we know about EEG signals. Also, beta and gamma activity does become stronger while having the eyes opened. But other than that, no other information could be deducted from the signals regarding the circumstances in which these signals were recorded.

B. Attention and Meditation

As mentioned in section III.B, MindWave Mobile also sends two 1-byte values that indicate the alertness and calmness of the user. We collected data in a relaxed state with closed eyes, and some of the data were collected while having the eyes opened. We show some of the collected averaged Attention and Meditation values in Table. I. While having the eyes closed the Meditation values did reached a higher value most of the time. But the Attention values were in most cases stuck around the value 50, and it was difficult to have it reach higher value than 50.

V. PROCESSING THE RAW DATA

A. Feature extraction of the signal

Using various feature extraction methods when processing EEG time-series data is a usual part of this field. Finding adequate methods is a widely researched area. These features usually are simple statistical features (mean, standard deviation) [27], [28]. Other more complex features are also frequently computed. One complex feature is the so-called Power Spectral Entropy (PSE) [29], [30]. Other notable feature for EEG analysis is Hjorth's features [31], [32].

We calculated some of these features on the raw data acquired in various circumstances. We gathered some of the results in Table. II. The data belonging to the first column (*Closed eyes 1*) was recorded while having the eyes closed and listening to upbeat music. The second one (*Closed eyes 2*) was recorded while listening to relaxed music. The *Open eye 1* and the *Open eye 2* were both recorded while having the eyes opened and listening to relaxing and upbeat music respectively.

Furthermore, *Open eye 1* was recorded while moderate concentration (reading) and *Open eye 2* were recorded while doing no particular task.

One can observe that every data's mean value was varied around the value 65. The standard deviation however is distinguishable regarding to the state of the eyes. This difference between having our eyes opened or closed is maintained in many of the described features. It can also be observed in some of the high order statistic features like skewness and kurtosis. Kurtosis measures whether the data is heavy- or light-tailed compared to that of normal distribution. Skewness measures the asymmetry of a probability distribution. Skewness for closed eyed data varied in the positive domain, while skewness for opened eye were usually around zero or below zero. Kurtosis for closed eye were much higher most of the time, which can be contributed to the fact that while having our eyes closed the range of values becomes smaller. Also, recordings while doing concentration-demanding tasks have usually higher number of zero-crossings, which can be contributed to the

TABLE I. EXAMPLES OF ATTENTION AND MEDITATION VALUES

	Attention	**Meditation**
Open eyes 1	48	61
Open eyes 2	52	53
Open eyes 3	50	50
Closed eyes 1	19	76
Closed eyes 2	75	64
Closed eyes 3	45	68

TABLE II. EXAMPLES OF EXTRACTED FEATURE VALUES

	Feature extraction values			
	Closed eyes 1	***Closed eyes 2***	***Open eyes 1***	***Open eyes 2***
Mean	65	65	65	65
Standard deviation	34	41	47	70
Difference between minimum and maximum value	1319	1542	1120	1678
Zero crossing rate	2048	1892	1631	4101
Spectral-centroid	45.25	43.6	41.8	37.0
Kurtosis	42	98	26	28
Skewness	0,06	4.64	-0.8	0.58
Petrosian Fractal Dimension	0.547	0.549	0.549	0.544
Hjorth's Mobility	0,0004	0,0004	0.0003	0,005
Hjorth's Complexity	2442	2383	2869	2043
Power spectral entropy	0.72	0.71	0.70	0.73

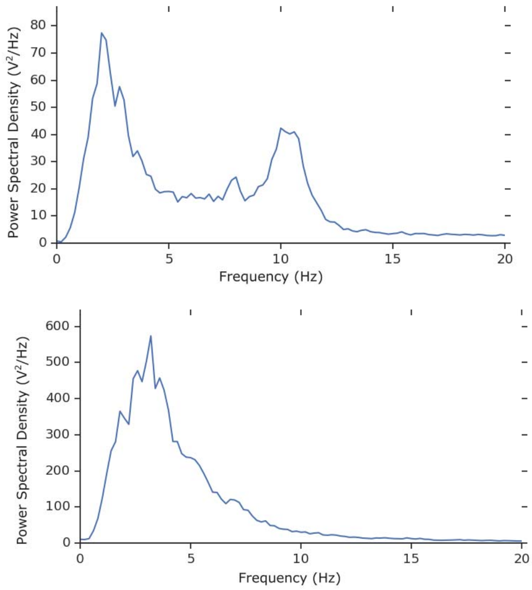

Fig. 2. Power spectral density of two different data.

fact that while concentrating we blink less and blinking usually causes big changes in the signal. But other than that, sharp contrast between the features of the various recordings is not present.

B. Frequency-domain analysis

As mentioned previously, changes in the magnitude or power of the EEG waves can hold information about the circumstances in which the data were recorded.

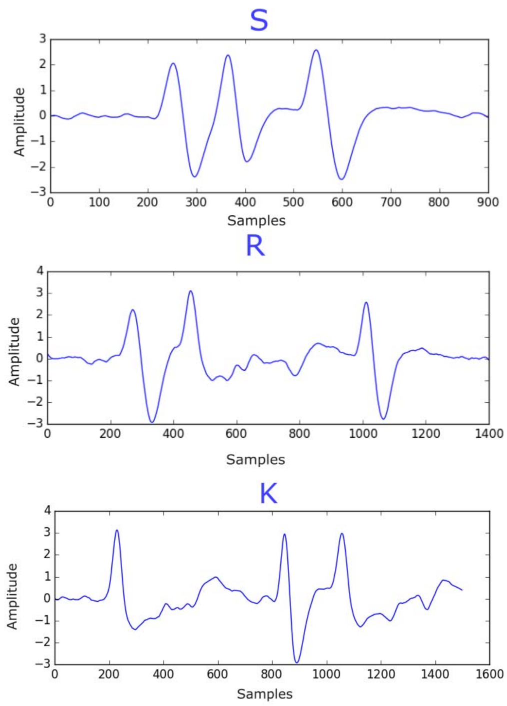

Fig. 3. Three patterns of blinking. First one represents *s*, second represents *r* and third represents *k*.

We tried to analyze data in the frequency-domain by plotting the Fourier-transform and the power spectral density of the signals. To compare two different type of data one can observe the power spectral density in Fig. 2. The first plotted data was recorded while having the wearer's eyes closed and the second one while having the eyes opened. We concluded that the state of the eyes has influence on the signal, the alpha bin gets more dominant when eyes are closed, and the frequency bin associated to beta and gamma also get more prominent. But other potentially influencing circumstances like listening to different kind of music or doing tasks that demands concentration are hard to notice in these plots and cannot be extracted accurately.

C. Processing data with neural networks

1) Neural networks and BCI

In the last few decades machine learning algorithms, especially neural networks have been applied to almost every field of science and technology imaginable. It has also reached the field of BCI. Y. Liu et al. [33] used neural networks for monitoring the alertness and fatigue of a driver. Applications using convolutional neural networks (CNN) are getting increasingly popular in the last few years, and this trend also reached the processing of EEG signals. J. Zhang et al. [34] developed a method that uses deep-learning convolutional neural networks to classify imagined hand movements. X. Li et al. [35] used CNN-s and RNN-s (recurrent neural networks) for recognition of human emotions. H. K. Lee et al. [36] took on the task of measuring EEG data while performing visual experiments. Then they showed that methods based on CNN-s can achieve higher accuracy than traditional machine learning algorithms.

We also tried to apply neural networks on the processing of these data. We did that with the idea that maybe an algorithm can find patterns in the signal where human eyes cannot.

2) Recording while sound stimuli

For this experiment we have captured data with the following process. We recorded two classes of a data. The first class contains data that were recorded while playing an annoying, harsh sound for the wearer of the headset. The other class of data was recorded in a state where no sound was played. We wanted to find out whether a stimulus as harsh as this presents itself in the recorded signal.

First, we attempted to classify the following recorded data with a simple neural network by the means of the extracted features. We used the data bandpass filtered to the beta frequency as this is the frequency commonly present in the EEG of alert adult. We extracted the previously mentioned features from the signal and that became the input of our neural network. We created a simple neural network with one input layer, two hidden layers, and one output layer. We used ReLU (rectified linear unit) activation function in the layers except for the output layer, where we used sigmoid function. We had 120 samples, 60 positive (where a sound had been played) and 60 negative. We used 100 samples for training and 20 for testing. After numerous running we concluded that the neural network can validate the training data set with 65% accuracy and can classify the test data set with an average of 55% accuracy.

On the second approach we used the individual samples filtered to the beta frequency and made it as the input as is. The neural network used for this was identical to the first (other than the input dimensionalities). This succeeded more with validating the training set back (averaged around 85% accuracy), but the performance on the test data set was the same as previously (50%).

We also used a convolutional neural network for classifying the data as images rather than numerical data. We extracted the spectrograms from the samples and used them as the input of the network. It succeeded around the same accuracy as classifying the extracted features.

While processing the data with neural networks it became obvious that finding patterns in the signal is not an easy task, even with the help of neural networks. It succeeded on the raw, beta frequency data the best, but it is still far from getting a good classifier.

3) Recognizing patterns in blinking

Controlling devices with our minds can be achieved in more than one way. One way is to train machine learning algorithms to recognize imagined movements. Working with this device it became obvious that training like these cannot be achieved with it. But there is one type of pattern that was conspicuous and easily recognizable by even the human eye: blinking patterns.

We decided to run a simple experiment on the data. We recorded data while blinking a few characters of the Morse-code: *s*, *r*, and *k*. The letter *s* has the pattern of *short-short-short*, *r* is defined by *short-long-short*, and *k* is assigned to *long-short-long*. Three recording of these patterns can be seen in Fig. 3. The three patterns are distinguishable even with the human eye.

We decided to run this data through a neural network and confirm whether an algorithm can distinguish these patterns. We created a simple two-layer multiclass classification neural network. Then we recorded 10 of each pattern and used other previously recorded data for negative data. Thus, we obtained a 4-class classification. The results are promising. It could fully validate back the training data and running on new unseen data the network yielded promising results. It could extract the pattern *s* easily, and it could also extract the other two patterns with little error. It does have false positives, but with a larger training set it potentially could be used in real-time applications.

VI. Conclusion

In this paper we discussed different type of methods for analyzing data from a consumer-grade device. We concluded that using this one-channel device for complex EEG signal analysis is not viable. The obtained raw data is hard to analyze, it is noisy, and we cannot deduct concrete facts from it other than the general alertness of the user. So, it is not possible to use for BCI applications like recognizing imagined hand movements or recognizing any other concrete EEG pattern. But we did have promising results from recognizing blinking patterns. These type signals are easy to extract compared to any other information. They can probably be a good basis for controlling devices or robots, thus giving a platform for applications that may help disabled people.

References

[1] B. Rebsamen et al., "A Brain Controlled Wheelchair to Navigate in Familiar Environments," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 18, no. 6, pp. 590-598, Dec. 2010.

[2] T. Carlson and J. del R. Millan, "Brain-Controlled Wheelchairs: A Robotic Architecture," in IEEE Robotics and Automation Magazine, vol. 20, no. 1, pp. 65-73, March. 2013.

[3] R. Scherer, G. R. Muller, C. Neuper, B. Graimann and G. Pfurtscheller, "An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate," in IEEE Transactions on Biomedical Engineering, vol. 51, no. 6, pp. 979-984, June 2004.

[4] A. Jackson, C. T. Moritz, J. Mavoori, T. H. Lucas and E. E. Fetz, "The neurochip BCI: towards a neural prosthesis for upper limb function," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 14, no. 2, pp. 187-190, June 2006.

[5] G. R. Muller-Putz and G. Pfurtscheller, "Control of an Electrical Prosthesis With an SSVEP-Based BCI," in IEEE Transactions on Biomedical Engineering, vol. 55, no. 1, pp. 361-364, Jan. 2008.

[6] C. Lin et al., "Noninvasive Neural Prostheses Using Mobile and Wireless EEG," in Proceedings of the IEEE, vol. 96, no. 7, pp. 1167-1183, July 2008.

[7] C. Guger, W. Harkam, C. Hertnaes and G. Pfurtscheller. (1999, November). “Prosthetic Control by an EEG-based Brain- Computer Interface (BCI)”. In Proc. aaate 5th european conference for the advancement of assistive technology (pp. 3-6).

[8] C. Neuper, A. Schlögl, G. Pfurtscheller (1999, July), “Enhancement of Left-Right Sensorimotor EEG Differences During Feedback-Regulated Motor Imagery”, in Journal of Clinical Neurophysiology, vol. 16, no. 4, pp. 373-382

[9] F. Babiloni et al., "Linear classification of low-resolution EEG patterns produced by imagined hand movements," in IEEE Transactions on Rehabilitation Engineering, vol. 8, no. 2, pp. 186-188, June 2000.

[10] J. Kim, I. Kim, S. Haufe and S. Lee, "Brain-computer interface for smart vehicle: Detection of braking intention during simulated driving," 2014 International Winter Workshop on Brain-Computer Interface (BCI), Jeongsun-kun, 2014, pp. 1-3.

[11] C-T. Lin, R-C. Wu, S-F. Liang, W-H. Chao, Y-J. Chen and T-P. Jung, "EEG-based drowsiness estimation for safety driving using independent component analysis," in IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 52, no. 12, pp. 2726-2738, Dec. 2005.

[12] R. N. Khushaba, S. Kodagoda, S. Lal and G. Dissanayake, "Driver Drowsiness Classification Using Fuzzy Wavelet-Packet-Based Feature-Extraction Algorithm," in IEEE Transactions on Biomedical Engineering, vol. 58, no. 1, pp. 121-131, Jan. 2011.

[13] K. George, A. Iniguez and H. Donze, "Sensing and decoding of visual stimuli using commercial Brain Computer Interface technology," 2014 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings, Montevideo, 2014, pp. 1102-1104.

[14] A. Kline and J. Desai, "SIMULINK®based robotic hand control using Emotiv™ EEG headset," 2014 40th Annual Northeast Bioengineering Conference (NEBEC), Boston, MA, 2014, pp. 1-2.

[15] N. Chumerin, N. V. Manyakov, M. van Vliet, A. Robben, A. Combaz and M. M. Van Hulle, "Steady-State Visual Evoked Potential-Based Computer Gaming on a Consumer-Grade EEG Device," in IEEE Transactions on Computational Intelligence and AI in Games, vol. 5, no. 2, pp. 100-110, June 2013.

[16] C. Lin, C. Ding, C. Liu and Y. Liu, "Development of a real-time drowsiness warning system based on an embedded system," 2015 International Conference on Advanced Robotics and Intelligent Systems (ARIS), Taipei, 2015, pp. 1-4.

[17] C. A. Lim, Wai Chong Chia and Siew Wen Chin, "A mobile driver safety system: Analysis of single-channel EEG on drowsiness detection," 2014 International Conference on Computational Science and Technology (ICCST), Kota Kinabalu, 2014, pp. 1-5

[18] J. He, D. Liu, Z. Wan and C. Hu, "A noninvasive real-time driving fatigue detection technology based on left prefrontal Attention and Meditation EEG," 2014 International Conference on Multisensor

Fusion and Information Integration for Intelligent Systems (MFI), Beijing, 2014, pp. 1-6.

[19] J. W. Britton, L.C. Frey, J. L. Hopp et al., authors; E.K St. Louis., L.C. Frey, editors. Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants [Internet]. Chicago: American Epilepsy Society; 2016. The Abnormal EEG. Available from: https://www.ncbi.nlm.nih.gov/books/NBK390357/

[20] medicine.mcgill.ca, “EEG > alpha waves”, https://www.medicine.mcgill.ca/physio/vlab/biomed_signals/eeg_raw.htm [Accessed: 09-Nov-2018]

[21] E. Niedermeyer and F. H. Lopes da Silva, "Electroencephalography: Basic Principles, Clinical Applications, and Related Fields". Lippincott Williams & Wilkins, 2005, pp. 178-180

[22] S. J. M. Smith, “EEG in neurological conditions other than epilepsy: when does it help, what does it add?” in Journal of Neurology, Neurosurgery & Psychiatry, 2005, vol. 76, pp. ii8-ii12

[23] neurosky.com, "ATTENTION eSense", [Online]. Available: http://developer.neurosky.com/docs/doku.php?id=thinkgear_communications_protocol#attention_esense. [Accessed: 09-Nov-2018]

[24] neurosky.com, "MEDITATION eSense", [Online]. Available: http://developer.neurosky.com/docs/doku.php?id=thinkgear_communications_protocol#meditation_esense. [Accessed: 09-Nov-2018]

[25] neurosky.com, "ASIC_EEG_POWER_INT", [Online]. Available: http://developer.neurosky.com/docs/doku.php?id=thinkgear_communications_protocol#asic_eeg_power_int. [Accessed: 09-Nov-2018]

[26] neurosky.com, "EEG Band Power values: Units, Amplitudes, and Meaning", [Online]. Available: http://support.neurosky.com/kb/development-2/eeg-band-power-values-units-amplitudes-and-meaning. [Accessed: 09-Nov-2018]

[27] J. Suto, S. Oniga and P. P. Sitar, "Music stimuli recognition from electroencephalogram signal with machine learning," 2018 7th International Conference on Computers Communications and Control (ICCCC), Oradea, 2018, pp. 260-264.

[28] R. Jenke, A. Peer and M. Buss, "Feature Extraction and Selection for Emotion Recognition from EEG," in IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 327-339, 1 July-Sept. 2014.

[29] A. Zhang, B. Yang and L. Huang, "Feature Extraction of EEG Signals Using Power Spectral Entropy," 2008 International Conference on BioMedical Engineering and Informatics, Sanya, 2008, pp. 435-439.

[30] J Suto, S Oniga, "Efficiency investigation of artificial neural networks in human activity recognition" in Journal of Ambient Intelligence and Humanized Computing 9 (4), 1049-1060, August 2018

[31] B. Hjorth, "EEG analysis based on time domain properties" in Electroencephalography and Clinical Neurophysiology , Volume 29 , Issue 3 , 306 – 310

[32] S-H. Oh, Y-R. Lee, and H-N. Kim, "A Novel EEG Feature Extraction Method Using Hjorth Parameter" in International Journal of Electronics and Electrical Engineering, Vol. 2, No. 2, pp. 106-110, June 2014.

[33] Y. Liu, Y. Lin, S. Wu, C. Chuang and C. Lin, "Brain Dynamics in Predicting Driving Fatigue Using a Recurrent Self-Evolving Fuzzy Neural Network," in IEEE Transactions on Neural Networks and Learning Systems, vol. 27, no. 2, pp. 347-360, Feb. 2016.

[34] J. Zhang, C. Yan and X. Gong, "Deep convolutional neural network for decoding motor imagery based brain computer interface," 2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), Xiamen, 2017, pp. 1-5.

[35] X. Li, D. Song, P. Zhang, G. Yu, Y. Hou and B. Hu, "Emotion recognition from multi-channel EEG data through Convolutional Recurrent Neural Network," 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Shenzhen, 2016, pp. 352-359.

[36] H. K. Lee and Y. Choi, "A convolution neural networks scheme for classification of motor imagery EEG based on wavelet time-frequecy image," 2018 International Conference on Information Networking (ICOIN), Chiang Mai, 2018, pp. 906-909.