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Research Paper / Makale

Drowsiness Detection and Alert System Using Wearable Dry Electroencephalography for Safe Driving

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Abstract: Driver drowsiness and fatigue plays a great impact in causing road accidents. Drowsiness can lead to inattentiveness or even microsleep, which involves brief intermittent moments of sleep sometimes without the person even noticing it, and this can sometimes be fatal when driving. In this paper, a drowsiness detection an alert system is proposed to identify the drowsiness level of a driver and trigger an audible alarm, status display on LCD, and a light indicator to alert the driver. The input is captured using MindLink Neuro Sensor which is a wearable dry EEG headset which is wirelessly connected to the microcontroller. The common activities that activate certain brain wave, as well as the activities that deactivate the respective brain wave is examined and presented in the results. It can be seen that a few brain waves can be associated with drowsiness as they are triggered during yawning such as the alpha, beta, and theta waves, but the MindLink EEG headset used in this experiment featured 2 nodes placed at the front of the forehead and is most sensitive to changes in the alpha wave, so alpha wave is used as a drowsiness determinant.

Keywords: driver drowsiness, electroencephalography, brain computer interface

Güvenli Sürüş için Giyilebilir Kuru Elektroensefalografi Kullanan Uyuşukluk Algılama ve Uyarı Sistemi

Öz: Sürücünün uyuşukluk ve yorgunluğunun yol kazalarına neden olmada büyük etkisi vardır. Uyuşukluk, dikkatsizliğe ve hatta bazen kişinin farkına bile varmadan kısa aralıklı uyku anlarını içeren mikro uykuya yol açabilir ve bu bazen araba kullanırken ölümcül olabilir. Bu yazıda, sürücünün uykululuk seviyesini belirleyen, seviye artınca sesli bir alarmı çalıştıran, LCD'de uykululuk seviyesi durum göstergesi ve sürücüyü uyarmak için bir ışıklı göstergesi olan bir uyuşukluk algılama ve uyarı sistemi önerilmiştir. Veri girişi, mikrodenetleyiciye kablosuz olarak bağlanan giyilebilir bir kuru EEG kulaklığı olan MindLink Neuro Sensor kullanılarak sağlanmıştır. Belirli beyin dalgasını aktive eden ortak faaliyetler ve ilgili beyin dalgasını devre dışı bırakan aktiviteler incelenmiş ve sonuçlarda sunulmuştur. Alfa, beta ve teta dalgaları gibi birkaç beyin dalgasının esneme sırasında tetiklendikleri için uyuşukluk ile ilişkilendirilebileceği görülebilir, ancak bu deneyde kullanılan MindLink EEG kulaklığı alnın önüne yerleştirilmiş 2 düğüm içerdiği ve en çok alfa dalgasındaki değişikliklere duyarlı olduğu için Alfa beyin dalgaları uyku hali belirleyicisi olarak kullanılmıştır.

Anahtar Kelimeler: sürücü uyuşukluk, elektroensefalografi, beyin bilgisayar arayüzü

1. Introduction

Driver drowsiness and fatigue plays a great impact in causing road accidents. Drowsiness can lead to inattentiveness or even microsleep, which involves brief intermittent moments of sleep sometimes without the person even noticing it, and this can sometimes be fatal when driving. It is

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reported that 35%–45% of road accidents are caused by drowsy driving [1]. A lot of research is done in this area to provide an early warning to the driver if they are detected to experience drowsiness so that they can rest or take a break from driving [2–13].

Saini V. [14] and Li Z. [15] suggests that drowsiness detection systems typically fall under 4 different categories: 1. Electrocardiogram (ECG) and electroencephalography (EEG), 2. Local Binary Pattern (LBP), 3. Steering Wheel Movement (SWM), and 4. Optical detection.

The SWM method analyses the steering wheel movement data collected from sensors mounted on the steering lever based on the frequency of steering corrections. When a driver is in a drowsy state, the frequency of steering corrections decreases noticeably. To avoid the interference of lane-changing, researchers only measure small steering angles. The SWM method is very reliant on the geometrical features of the road and can only work reliably in limited situations [16–18]. Figure 1 illustrates the SWM method as implemented by Toyota in their vehicles.

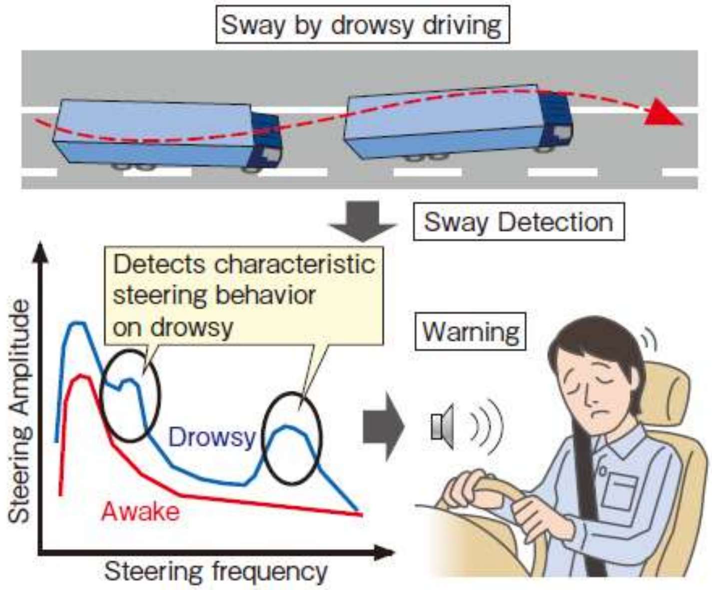


Figure 1. SWM method implemented by Toyota [19].

The EEG method has proven to be very accurate in detecting early stage of drowsiness. Among all the frequently used physiological signals, EEG showed the strongest relation with drowsiness [20]. Hence, EEG is widely considered as a reliable measure for drowsiness, fatigue, and performance evaluation. Awais M. in [21] conducted experiments to observe the significant changes that occur in the EEG power spectrum during monotonous driving and found that brain signals provide a promising drowsiness indicator which can be used to prevent road accidents caused by driver drowsiness. The EEG sensor detects and amplifies the small voltages of electricity generated by the brain cells (neurons) when they fire. Neurons from different locations can fire in the same way as muscle fibres. The most frequently found frequencies, for EEG, are between 1 Hz and 40 Hz. The EEG sensor captures a raw EEG signal, which is the continuously changing potential difference between the positive and negative electrode, and the program uses the signal to obtain frequency-domain information by adding a series of digital filters to the reported signal. Oviyaa M. [22] developed a real-time system that tracks and examines the driver's EEG signal using an EEG headset. When the driver is nearly in the drowsy stage, an alarm is triggered. The result gives an accuracy of 97.6% to recognize sleep in test of 60 participants. The method is found to be affordable, time-efficient, and less complex compared to other similar methods [23]. The understanding of sensitive brain part among different frequency bands also helps lower the number of electrodes needed to establish an efficient EEG-based drowsiness detection [20].

EEG reading is a completely safe procedure that can be conducted repeatedly on patients, normal adults, and children without any risk or limitation. The local current flow is caused by active neurons consisting of Na+, K+, Ca++, and Cl− ions that are expelled through channels in neuron membranes in the direction governed by membrane potential. The recordable electrical activity is created on the head surface. Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves can be found in Figure 2 [24]

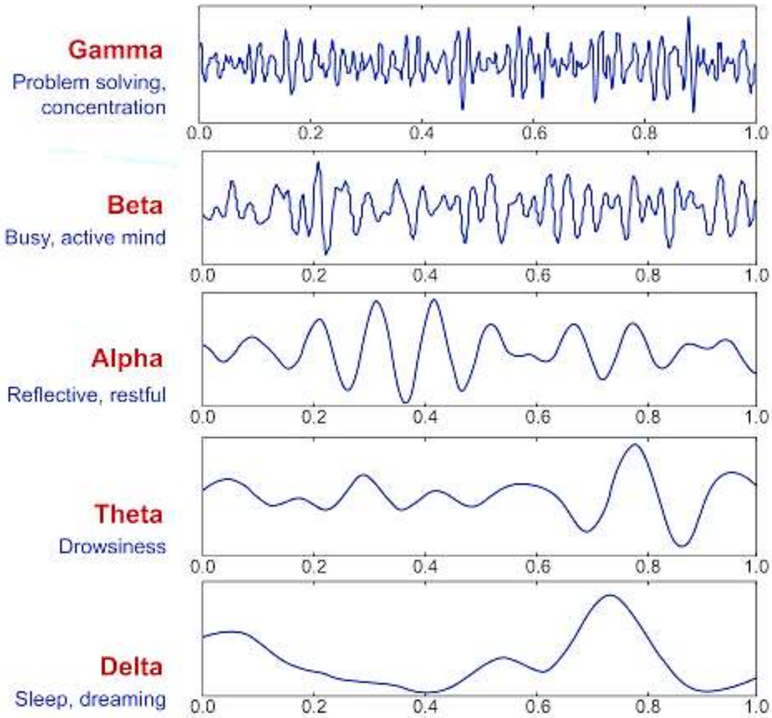


Figure 2. Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves [25].

Brain waves change based on the activity the subject is doing and feeling [26]. Feeling tired, exhausted, slow, or dreamy show slower brainwaves are dominant. Otherwise, feeling strong and hyper-alert shows higher brain waves are dominant. The wave of activity range of alpha is from 8 Hz and 13 Hz. Located at occipital, parietal, and posterior temporal as the most prominent region. The state for this band is relaxed, wakefulness with eyes closed. Frequency of 8 Hz to 4 Hz is the theta band, and it is normal for adults to have little amount of theta wave compared to infants or when the adult is asleep. Frequency below 0.5 Hz to 4 Hz is known as delta band; deep sleep or anaesthesia are present in this band [27]. Theta wave is categorized as a slow signal activity, and it occurs during irregular awake of adults [28]. The theta band frequency can range from 4 Hz until 7 Hz. Alpha wave is the primary signal that can be viewed in normal relaxed adult and regularly occur in children over the age of thirteen. The frequency range is between 8 Hz and 12 Hz, and it is dominant in the posterior area of the skull [13] Beta wave usually occurs to those who are restless and on alert with a frequency between 14 Hz to 40 Hz.

2. Experimental Methods

Figure 3 illustrates the block diagram of the proposed system. The input is captured using MindLink Neuro Sensor which can be seen in Figure 4, a wearable dry EEG headset connected wirelessly to the microcontroller via Bluetooth. Arduino Uno is the microcontroller that will process incoming data from the EEG headset and determine the current condition of the driver. If drowsiness is detected, an alarm will be triggered to alert the driver and prevent further tragedy.

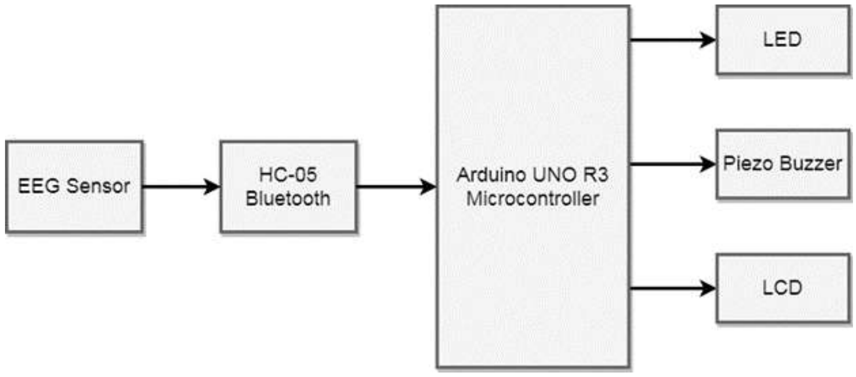


Figure 3. Block diagram of the proposed system.

Figure 4. The MindLink Neuro Sensor.

From the block diagram, the hardware implementation is then put together for a simple simulation to determine it is all working as intended before moving into the actual hardware as shown in Figure 5.

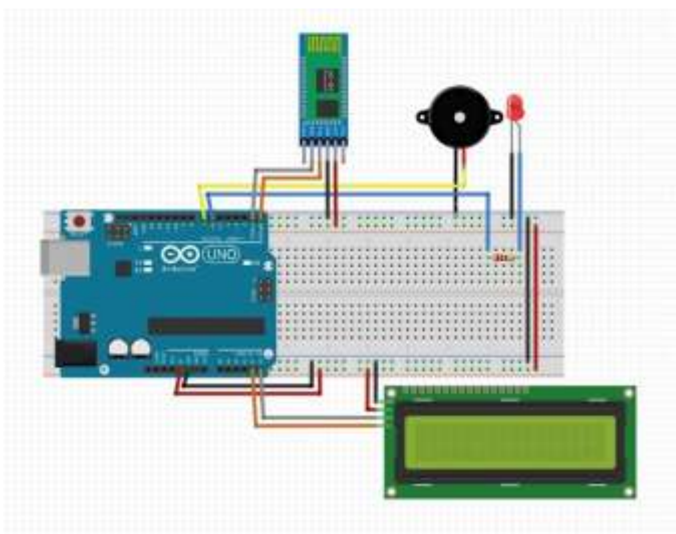


Figure 5. The simulated hardware implementation of the system.

3. Results and Discussion

After the hardware components and the software procedures are integrated, it is time to test the system. When the EEG headset is turned on, initially it will flash its red LED as in Figure 6 indicating that the device is waiting to be paired with a master device, and in this project, the Arduinomicrocontroller via HC-05 Bluetooth module. Once the pairing is complete and the handshake process is successful, the EEG headset will light its blue LED as in Figure 7.

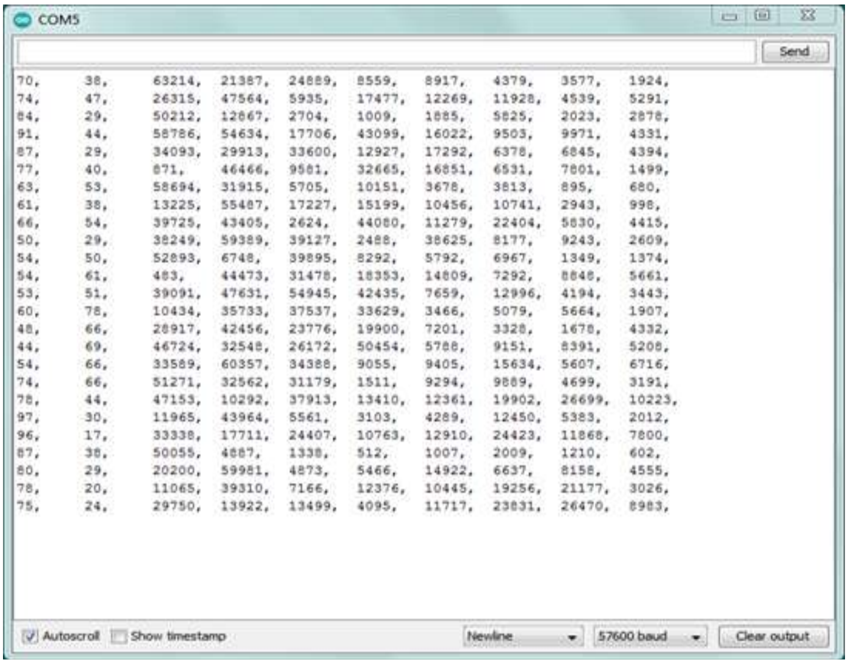
Figure 6. MindLink EEG red LED flashing.

Figure 7. MindLink EEG blue LED flashing.

The user can now wear the headset. Make sure the metal nodes are directly placed on the forehead to get accurate sensor data as illustrated in Figure 8. When the EEG headset starts getting valid signal from the brain, it will sound 2 short beeps to acknowledge that the headset is indeed worn properly.

Figure 8. The headset is worn by making sure the metal nodes directly touch the forehead.

In earlier experiments done using other type of EEG headset [26] like the Mindflex EEG headset, the sensor only provides raw data to the system, so additional calculations must be done by the controller using the equations derived by Nunez [29]. The MindLink EEG headset however already did the Fourier transform, and this can be seen in Figure 9 where the data sent is separated into different channels. This can be converted into a graph for better interpretation as depicted in Figure 10.



70,	38,	63214,	21387,	24889,	8559,	8917,	4379,	3577,	1924,
74,	47,	26315,	47564,	5935,	17477,	12269,	11928,	4539,	5291,
84,	29,	50212,	12867,	2704,	1009,	1885,	5825,	2023,	2878,
91,	44,	58786,	54634,	17706,	43099,	16022,	9503,	9971,	4331,
87,	29,	34093,	29913,	33600,	12927,	17292,	6378,	6845,	4394,
77,	40,	871,	46466,	9581,	32665,	16851,	6531,	7801,	1499,
63,	53,	58694,	31915,	5705,	10151,	3678,	3813,	895,	680,
61,	38,	13225,	55487,	17227,	15199,	10456,	10741,	2943,	998,
66,	54,	39725,	43405,	2624,	44080,	11279,	22404,	5830,	4415,
50,	29,	38249,	59389,	39127,	2488,	38625,	8177,	9243,	2609,
54,	50,	52893,	6748,	39895,	8292,	5792,	6967,	1349,	1374,
54,	61,	483,	44473,	31478,	18353,	14809,	7292,	8848,	5661,
53,	51,	39091,	47631,	54945,	42435,	7659,	12996,	4194,	3443,
60,	78,	10434,	35733,	37537,	33629,	3466,	5079,	5664,	1907,
48,	66,	28917,	42456,	23776,	19900,	7201,	3328,	1678,	4332,
44,	69,	46724,	32548,	26172,	50454,	5788,	9151,	8391,	5208,
54,	66,	33589,	60357,	34388,	9055,	9405,	15634,	5607,	6716,
74,	66,	51271,	32562,	31179,	1511,	9294,	9889,	4699,	3191,
78,	44,	47153,	10292,	37913,	13410,	12361,	19902,	26699,	10223,
97,	30,	11965,	43964,	5561,	3103,	4289,	12450,	5383,	2012,
96,	17,	33338,	17711,	24407,	10763,	12910,	24423,	11868,	7800,
87,	38,	50055,	4887,	1338,	512,	1007,	2009,	1210,	602,
80,	29,	20200,	59981,	4873,	5466,	14922,	6637,	8158,	4555,
78,	20,	11065,	39310,	7166,	12376,	10445,	19256,	21177,	3026,
75,	24,	29750,	13922,	13499,	4095,	11717,	23831,	26470,	8983,

Figure 9. Raw data sent by MindLink EEG headset.

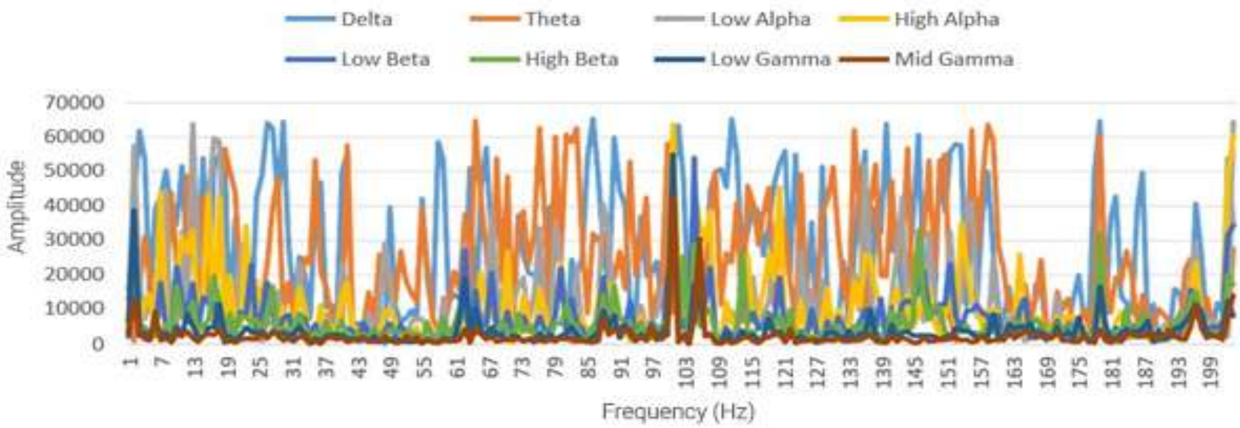


Figure 10. Visualizing the 8 signal wave changes with time.

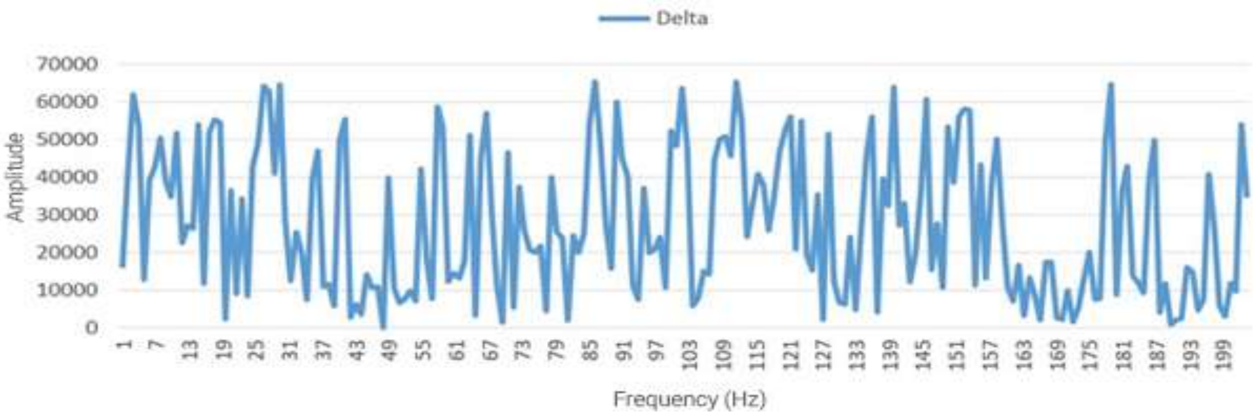


Figure 11. Delta wave read from the EEG while doing activities.

Test subjects are then instructed to do basic activities such as sitting down, lying down, closing eyes, opening eyes, blink normally, blink faster, among others and their brain signals are recorded. The observed graphs while doing these activities are as illustrated in Figure 11, Figure 12, Figure 13, Figure 14, and Figure 15, respectively.

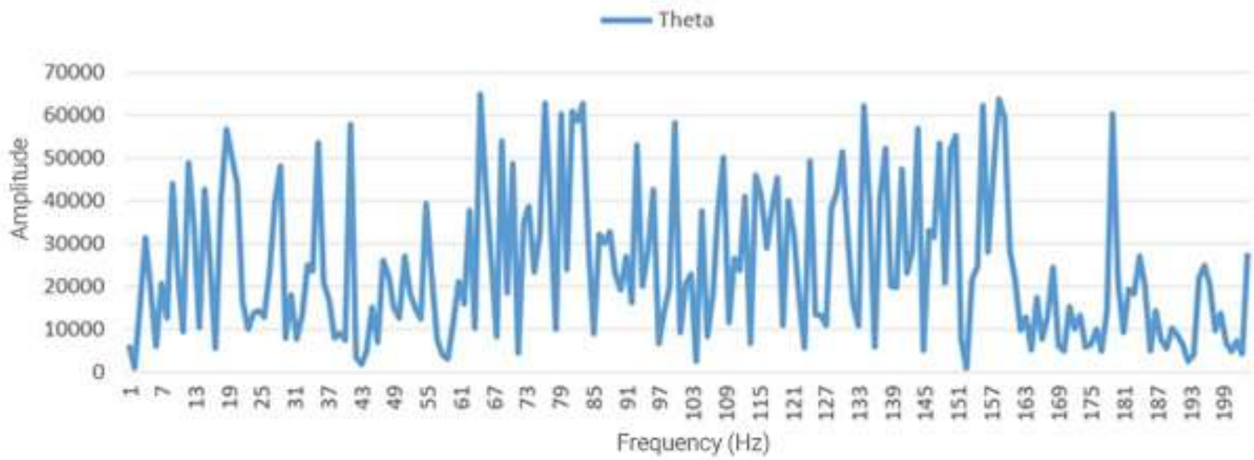


Figure 12. Theta wave read from the EEG while doing activities.

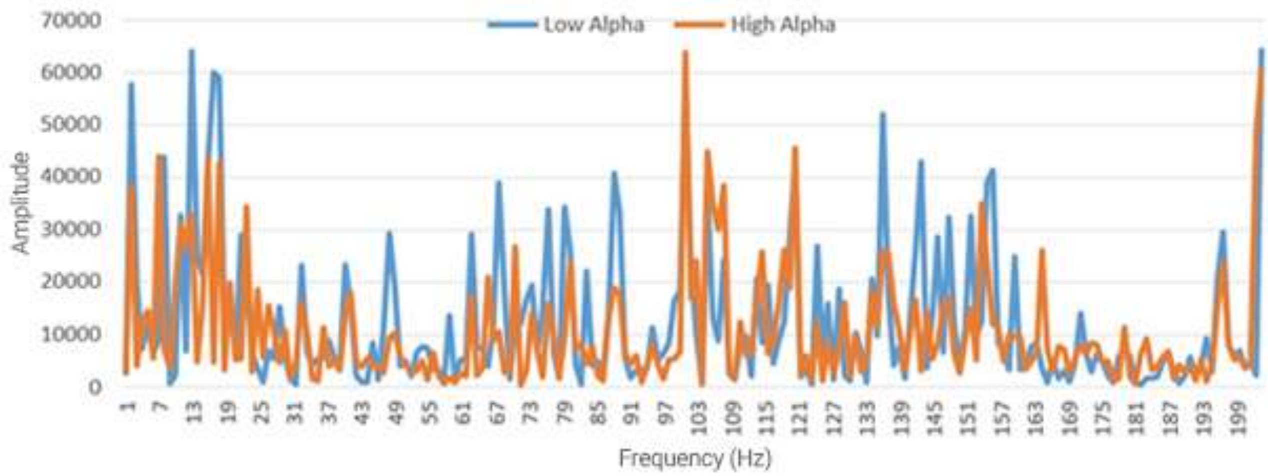


Figure 13. Alpha waves read from the EEG while doing activities.

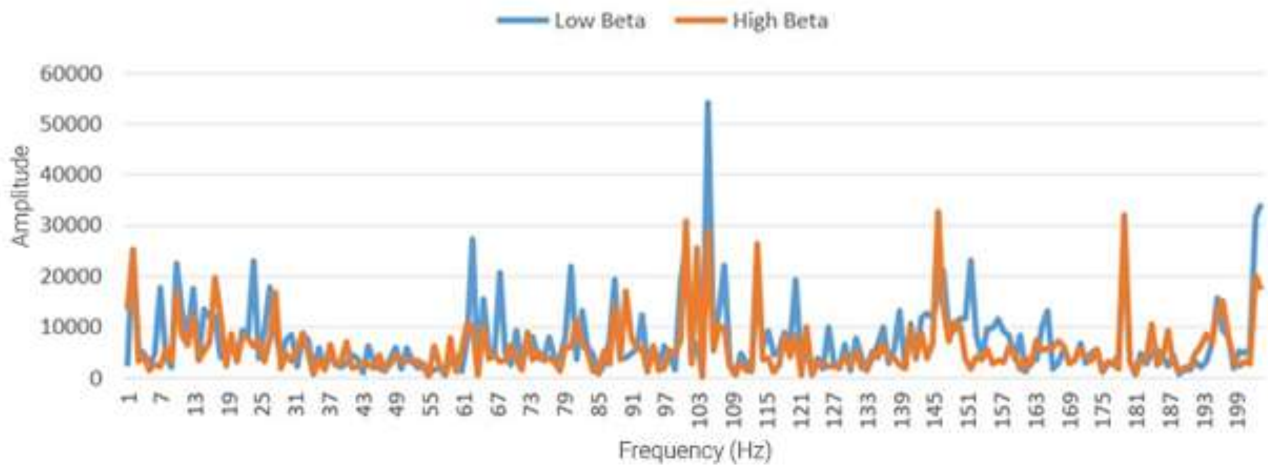


Figure 14. Beta waves read from the EEG while doing activities.

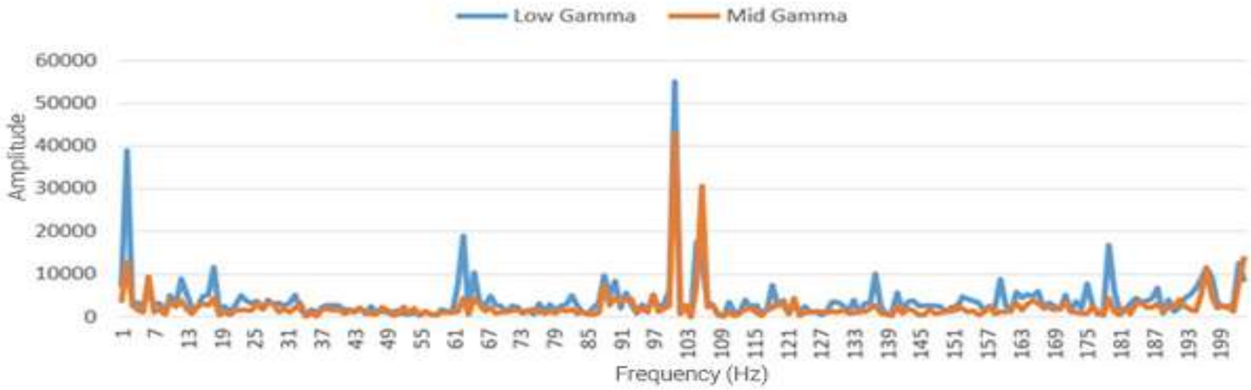


Figure 15. Gamma waves read from the EEG while doing activities.

From the experiments done, the dominant values for each brain wave are compiled in Table 1. The activities that activate certain brain wave, as well as the activities that deactivate the respective brain wave is also examined and presented in Table 2. It can be seen that a few brain waves can be associated with drowsiness as they are triggered during yawning, but the MindLink EEG headset used featured 2 nodes placed at the front of the forehead, and it is most sensitive to changes in the alpha wave, so for this experiment, focus is given to the alpha wave to determine drowsiness.

Table 1. The detected brain waves with its dominant amplitudes read from the EEG.

Attention	Mediation	Delta	Theta	Low Alpha
70	38	63,214	21,387	24,889
High Alpha	**Low Beta**	**High Beta**	**Low Gamma**	**High Gamma**
8,559	8,917	4,379	3,577	1,924

Table 2. Brain waves and the associated activities that activate or deactivate them.

Brain Waves	Activate	Deactivate
Delta	Walking, focusing, slow blinking eyes, yawning, fast blinking eyes.	Lie down with eyes closed.
Theta	Slow blinking eyes, yawning, fast blinking eyes.	Walking, focusing, lie down with eyes closed.
Low Alpha	Walking, slow blinking eyes, fast blinking eyes.	Focusing, yawning, lie down with eyes closed.
High Alpha	Walking, slow blinking eyes, yawning.	Focusing, fast blinking eyes, lie down with eyes closed.
Low Beta	Walking, yawning.	Focusing, slow blinking eyes, fast blinking eyes, lie down with eyes closed.
High Beta	Walking, yawning.	Focusing, slow blinking eyes, fast blinking eyes, lie down with eyes closed.
Low Gamma	Yawning, lie down with eyes closed.	Walking, focusing, slow blinking eyes, fast blinking eyes.
Mid Gamma	Yawning.	Walking, focusing, slow blinking eyes, fast blinking eyes, lie down with eyes closed.

Figure 16 shows the differences between awake state and drowsiness state in the combined alpha wave. In the awake state, the graph fluctuates with a much lower frequency and with a smaller number of peaks, and the peaks are at a lower height than the drowsiness state. On the other hand, in the drowsiness state, the graph fluctuates at a much higher frequency, with more peaks and the peaks can reach higher apex than the ones in the awake state. Once the software is trained to recognize this, an alarm can be successfully triggered once the system determines that a drowsiness state is taking place.

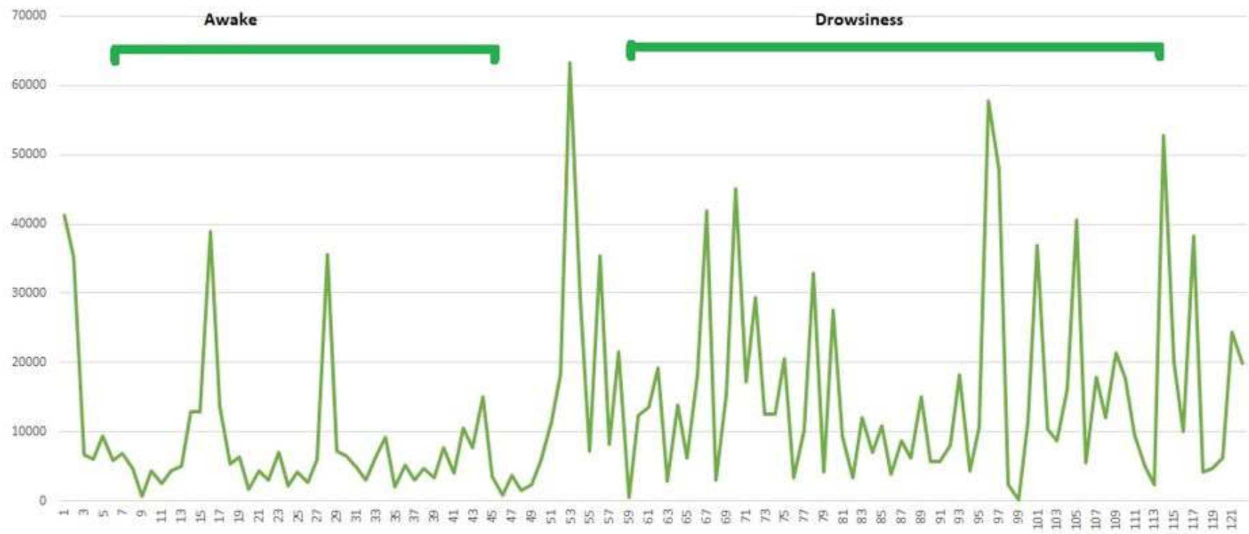


Figure 16. The difference between awake and drowsiness state in the alpha wave.

4. Conclusions

The aim of this research is to create a system that utilizes a dry wearable EEG sensor to identify drowsiness in drivers by reading driver's brain wave signals. The EEG headset connects to the microcontroller wirelessly, so it does not interfere with the driver's operating environment. The EEG sensor will read the driver's brain signal and send it to the microcontroller via Bluetooth and these data is evaluated to determine whether drowsiness is occurring. If so, an alert will be triggered to the driver and the driver can take the necessary actions to keep himself awake by resting or stop driving altogether and prevent a fatal accident. Another point worth considering is the project's magnitude in comparison to a real medical system. When compared to a full-scale medical apparatus, using just two basic electrodes with a homemade amplification circuit and related filtering was not a factor to disregard. With requirements of at least 75 scalp electrodes instituted in 1991 by the American EEG society as a part of the modified combinatorial nomenclature regarding EEG, a subtle amount of 2 electrodes proved elusive. Given the preceding observations, it is recommended that a more tried-and-true approach to obtain the signals is chosen, keeping in mind that creating a new one from scratch takes a lot of time and work. However, the project gave the members a good educational experience.

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Authors' Contributions

SF designed the outlining structure and wrote up the article. MA carried out the experimental work. KA computed the theoretical calculations. AF and MS fabricated the device. RA grew the sample according to the specifications. All authors have read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

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