

## Real-Time Driving Monitor System: Combined Cloud Database with GPS

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### Abstract

*In recent years, EEG brainwave-reading device is used more and more in various academic fields and real life. Analyzing brainwave from drivers, we divide the brainwave data into light fatigue, medium fatigue and severe fatigue. Once the driver's Low- $\alpha < 0.7$ , High- $\alpha < 0.5$ ,  $\theta > 0.5$ , or attention and meditation less than 40 degrees, then the system is determined that the driver is lethargic or inattention. The system will be based on the status of the different layers of the driving fatigue, showing the red, yellow and green lights warning message. Use the mobile device to alert the driver, and record the information in the database. In addition, the system is collocated with GPS positioning function. The user's brainwaves and GPS data will be integrated and analyzed after uploaded to the cloud server, to remind drivers if there are dangerous drivers within a radius of 20 meters what should be aware of.*

### 1. Introduction

A 2013 report by the World Health Organization (WHO) shows that about 1.24 million people die as a result of road traffic crashes around the world [1]. The US National Highway Traffic Safety Administration (NHTSA) estimated that fatigue driving was a factor in 2.2 to 2.6 percent of total fatal crashes annually during the period 2005 through 2009 [2]. In Europe, statistics show that 10% to 20% of all traffic accidents are caused by drivers with a diminished level of vigilance [3]. Fatigued drivers have become a serious road safety problem for society.

In the last decade, many studies have developed a variety of advanced driver assistance systems. However, most research has focused on monitoring the vehicle systems, like collision avoidance systems, lane departure warning systems, and autonomous cruise control systems. There has been less development on systems for monitoring driver status. In fact,

maintaining proper driver attention reduces the probability of traffic accidents.

The main methods used for measuring driver status can be divided into three types [7]: Electroencephalograph (EEG) methods that use a headband device in which the electrodes are embedded to make contact with the driver's scalp to measure brain waves; Ocular measurements that use a camera to detect eye-blinking, pupil-response, eye-closure, and eye-movement; and physiological or biobehavioral measures that monitor the tone of facial muscles (facial expression), body postures, blink frequency, eyes closed amplitude, changes in blood pressure, and head nodding.

The EEG algorithm monitors the spontaneous bioelectrical activity of the brain. By collecting, filtering, transforming, and analyzing these signals, we can interpret the real-time state of a driver. The EEG has also been studied to detect drowsiness, but most of these studies have used the EEG to validate the existence of drowsiness when other measures are being evaluated rather than as a fatigue detection measure [4][5]. EEG machines are too heavy and not fit for use in cars. The biggest drawback associated with EEG as an on-road drowsiness detection device is the difficulty in obtaining recordings under natural driving conditions, making it a somewhat unrealistic option for the detection of fatigue [6]. But in this paper, we use a new product call the "NeuroSky MindWave Headset" which can collect a user's EEG signal value with a single chip. This device is lightweight and portable, so it is well-suited for wearing while driving.

As a result of the development of cloud computing and wireless connections, the cloud database and GPS can be integrated into a real-time monitoring system. By storing and analyzing driver fatigue data, the system can warn drivers in a dangerous state and inform the preset contacts of the driver's fatigue level and location in time if the driver does not react appropriately. The purpose of this paper is to build an

immediate monitor that can accurately identify a driver's state of fatigue and prevent drivers from causing car accidents.

This study was conducted to build a real-time driver fatigue monitoring system. We used the brain wave Low- $\alpha$ , High- $\alpha$ , and  $\theta$  values to determine the fatigue level and the car's position was obtained using a Global Positioning System (GPS) receiver. The user's fatigue level will be calculated by fatigue warning system and alert the user when the fatigue is detected. And we also use High- $\beta$  to know whether the driver encounters unexpected situations or not and send the message to the user's contact person. The system will inform user's designated contact that the user is at the driving risk. The user's GPS position and fatigue level will be stored in the cloud sever. The cloud data can help other drivers to know whether there is a fatigued driver nearby.

2. Theoretical Background

2.1 What is a Brainwave?

Our brains are organized into billions of brain cells with neurons. These neurons interact and become weak electrical pulses. The electrical potential difference made by the cerebral cortex can be measured with sensitive medical instruments. The frequency of human brainwaves can change in different situations like sleep or emotional arousal. The normal intensity of brainwaves is under 100uV, and their frequency is usually between 0.1Hz~40Hz.

2.2 Brainwave Type Categories

According to the International Federation of Societies for Electroencephalography and Clinical Neurophysiology [11], brainwaves fall into several categories:

Table 1. Brainwave Type Categories

Brainwave Type	Frequency
	Feature
Beta activity ( $\beta$ wave)	12.5 Hz – 30 Hz
	Beta waves regularly appear in the frontal region while people are awake. This is especially noticeable when the brain is thinking or stimulated by the senses.
Alpha activity	7.5 Hz – 12.5 Hz

( $\alpha$ wave)	Alpha waves are neural oscillations arising from synchronous and coherent (in phase or constructive) electrical activity of thalamic pacemaker cells in humans. These waves disappear when people have their eyes open, are thinking, or are being stimulated by other means. Relaxing with closed eyes will generally lead to the appearance of $\alpha$ waves.
Theta activity ( $\theta$ wave)	4 Hz – 7 Hz
	Theta waves occur mostly in the subconscious mind, influencing attitude and behavior. These brain waves usually occur when a person is dozing off or in a light sleep state.
Delta activity ( $\delta$ wave)	0 Hz – 4 Hz
	There is almost no delta wave activity in an awake adult. This brain wave occurs in deep sleep and unconscious states.

2.3 Attention

As an issue of cognitive psychology, attention refers to how people deal with a variety of information in their current environment, and can also be known as limited resource allocation [12]. While driving a car, a driver is bombarded with sounds, scenery, and memories, as well as conversations with other passengers. Even though the driver is surrounded by these various sensations, it is still necessary to focus on driving the car.

As Psychologist William James states, attention is a brain process that deals with static and dynamic information to create a list of processes before handling several task. This sequence involves efficiently handling information and giving up some tasks to focus on others [13].

We often divide attention into two broad categories: involuntary attention and voluntary attention [17-20]. Voluntary attention refers to that state in which the brain cannot accurately accept all environmental information because it is currently handling another primary activity with some purpose. This type attention is critically important when performing certain tasks or dealing with problems. However, it isn't easy to maintain attention, and as time passes, attempting to maintain voluntary attention leads to mental fatigue.

Involuntary attention refers to simple attention without forcing [21]. Human senses allow the brain to be involuntarily attentive to many environmental influences like airplanes in the sky, strangers or animals on the street, or even glowing objects.

A study in 2010 that analyzed 100 cars found that lack of attention leads to 80% of traffic accidents and distractions leads to 65% of rearward bump accidents [14].

Unfortunately, the problems could worsen as a result of the technological development of wireless devices. Cell phones, personal tablets, and laptops become killers of traffic [15]. Drivers can easily be distracted by these and other modern handheld electronic devices that cause them to make irreparable mistakes.

According to the preceding discussion, it is clear that drivers must maintain a continuous and focused state of voluntary attention on the act of driving in traffic. Therefore, this research attempts to measure and detect fatigue with brainwave features and then offer real-time support to drivers.

## 2.4 The NeuroSky MindWave Headset

In recent years, NueroSky has committed to the development of a lightweight brain-computer interface device, as shown in Figure 1. Placed on the head to acquire the prefrontal brain EEG signal, the reference electrode and the circuit grounding system are connected to the left ear lobe, and the sampling frequency is 512 Hz.

The integrated ThinkGear™ chip is used to acquire the EEG signal, then filter, transform, analyze, and perform other digital signal processing functions. The device then uses the eSense™ algorithms to convert the user's EEG signal into attention and meditation. This research will integrate this device and its accompanying eSense™ algorithms for detecting EEG signals in drivers.



Figure 1. NeuroSky MindWave [16]

## 3. Related Works

### 3.1 Fatigue Detection Based on Driving Behavior

The current fatigue driving detection method usually involves brainwave or driver status. By collecting various data from the driver, it will be possible to determine if the driver is fatigued. The first study set up sensors on the pedals, seat, steering wheel, and gearshift of the car, collecting how the driver interacts with these components [8]. The data includes pedal movement, steering wheel rotation angles, accelerator pedal timing, and so on, which is sent to a PC for analysis. In order to prevent subjects from creating traffic accidents during the experiment, the researchers used a Logitech G27 system to simulate real driving. The researchers sent 176 subjects for the research and found that changes of the steering wheel and accelerator pedal were the most important factors impacting driving fatigue.

### 3.2 Fatigue Recognition Using Image Processing

The second study used facial expression to detect fatigue [9]. It is well known that people tend to close or blink their eyes when they are drowsy. This study detected facial expression changes like head tilt and eye closure as determinant factors. Because they use a common camera as a monitor to detect the driver's face, so the researchers developed a facial detection system to do this. A road lane detection system was also developed to determine when the drowsy driver could not prevent the car from approaching another lane more than usual. The researchers used these two systems to develop this fatigue detection study.

### 3.3 Fatigue Detection Using Wavelet Transform

The third study attempted to detect fatigue driving by a wavelet analysis of vehicle parameters [10]. Similar to the first study, researchers took advantage of the VR-4 driving simulator. The system used in this study was produced by the research team, giving real-time feedback to the driver through technological devices. The experiment collected data like vehicle speed, steering wheel angle, the state of accelerator, and so on. Then the data was divided into 100-second units and transformed into several segments, providing a visual line chart. Subjecting the original data to noise reduction and resampling dramatically increased the accuracy of the data. This study showed that it was feasible to use wavelet analysis to detect driver fatigue.

### 3.4 Drowsiness Detection System

The fourth study used the number of eyes closures and the brainwave value changes to detect fatigue driving [22]. This index was based on the assignment of points to brain waves, blinking, and facial expressions. The specific procedure for rating these three factors is shown in Figure 2. As a person's level of alertness drops, a large number of  $\alpha 2$  waves appear and then demonstrate larger amplitude. Blinking was rated by evaluating the measured waveforms for the upper and lower electric potential of the eyes. In a normal state of alertness, blinking appears as sharp spikes in the waveform. As the level of alertness drops, the spikes appear more frequently and subsequently lose their shape and become a gentle waveform when a person becomes drowsy. Eventually, the waveform shows trapezoidal shapes, indicating that the eyes close for long intervals.

Rank	Brain waves	Blinking	Facial expression
3	No $\alpha 2$ waves	Continuous rapid blinking	Rigid face muscles
2	Clusters of small amplitude $\alpha 2$ waves	Appearance of slow blinking	Drooping of upper eyelids
1	Continuous appearance of large-amplitude $\alpha 2$ waves	Eyes close for long intervals	Eyes half-closed

Figure 2. Evaluation Criteria for Brain Waves, Blinking and Facial Expressions

### 3.5 Approach to Retrieve Information on Driver's Fatigue by Integrating EEG, ECG, and Blood Biomarker

The fifth study considered blood and EEG readings [23]. They collected blood data from the subjects before the experiment began. The experiment lasted 32.5 hours, comprising 5 stages. Each stage lasted 3 hours and repeated until most of the subjects complained of extreme fatigue. These stages include simulated driving on a PC, walking on a treadmill, and other auditory and visual tasks, in order to generate different types of fatigue. The data were then calculated to determine whether a relationship exists between these data and fatigue.

## 4. Methodologies

### 4.1 Data Analysis

To analyze driver fatigue, this study measured the attention and meditation levels as reported by the Mindwave™ device. To improve accuracy, this study used three mindwaves like High- $\alpha$ , Low- $\alpha$  and  $\theta$  acquired from the raw data and calculated through cross references based on them.

### 4.2 Experimental Design

Performing this test to determine driver fatigue in a real-world driving situation was potentially dangerous and time-consuming. As an alternative, this study simulated then analyzed four situations. Table 2 shows these four situations:

Table 2. Simulated Situations

NO.	Simulated Situation
1	Being awake for 3~4 hours after 8 hours sleep (default waking state)
2	Waking up after 8 hours sleep
3	Mentally fatigued, after studying for 2~3 hours
4	Physically fatigued, after jogging or weight training.

Table 3. Attention and Meditation Levels

	Attention	Meditation
1~20	It means user is distraction and agitation.	It means user is very nervous and can't relax itself.
20~40	The user gradually loses attention and tends to distraction.	The user is increasingly nervous, wandering thoughts and anxiety.
40~60	This level is considered normal.	
60~80	The user gradually strengthens attention.	The user gradually loses his/her brain activity.
80~100	The user is very focused.	User brain information processing capacity is very low.

These situations represent common fatigue conditions affecting drivers, so simulating and analyzing them provides a strong dataset of real-world conditions. Situation 1 is a default waking state used as a control to be measured against situation 2, situation 3, and situation 4, all of which will collect fatigue data.

To determine whether the subject is genuinely fatigued, two methods will be used to assist the

judgment. First, the eSense™ algorithm developed by NeuroSky will specify whether the state is attention or meditation.

Attention indicates the intensity of a subject's level of mental "focus" or "attention", such as whether the driver was attracted by the scenery or other things while driving, leading to a state of distraction. Meditation indicates the level of a subject's mental "calmness" or "relaxation". Specifically, meditation refers to psychological relaxation rather than physiological relaxation. If the subject simply relaxes muscles or exhales deeply, this will not immediately have a great change on the state of meditation, which is related to active mental processes in the brain. The amount of processing power that the brain dedicates to analyzing image information is reduced when the eyes are closed, so this is often an effective method for increasing the level of meditation.

In addition to verbal confirmation, we also asked subjects to wear a MindWave device to collect data for one minute. The average attention level was calculated in this minute through an algorithm provided by the device. If the eSense™ algorithm value of attention was lower than 40 while meditation was higher than 60, the subject was considered fatigued. Other readings showed the subject to be awake. The NeuroSky MindWave Mobile device was used to collect all the MindWave readings.

Neurosky MindWave Mobile is an EEG brainwave sensor, making the detection of brainwave patterns easier than traditional EEG devices. The MindWave value was sent to the cell phone layout from the device through Bluetooth technology and saved as an XML file.

The 28 subjects who participated in this experiment were recruited from the National Chung Cheng University in Taiwan. The gender ratio was about 1:1 and half of the subjects were between 20 to 30 years old, while the other half were between 30 to 40 years old. The data from these 28 subjects provided 500 sample data points for each scenario to provide an overview of each fatigue condition.

The second method used to determine if the subject was fatigued involved a series of mathematical questions. Subjects were asked to complete four series containing five questions of simple arithmetic. Two series included the multiplication of two digits numbers, while the others were addition or subtraction of five digits numbers. The values used in these questions were randomly selected and the total number of questions was 20. The subject was required to answer each question within 10 second or it would be considered wrong. During this process, the subjects wore the MindWave device and researchers monitored the changes in brainwave patterns. This experiment

was used to confirm the subject's level of fatigue. If the time required for the subject to answer these questions was longer than the time required during the subject's default awake situation, then the subject was determined to be fatigued.

Fig. 3, Fig. 4, and Fig. 5 show the results of each subject's simulated situations using the eSense™ algorithm and math questions. This study captured the Low- $\alpha$ , High- $\alpha$ , and  $\theta$  values of each subject for comparison. Because the value was already Fourier transformed by the device, the value has no unit of measure.

Fig. 3, Fig. 4, and Fig. 5 show the results of four situations which compare the values of High- $\alpha$ , Low- $\alpha$ , and  $\theta$  between awake and fatigue states. The x-axis presents the number of each subject, while the y-axis shows the values returned from the MindWave device. The red line represents the subject's High- $\alpha$ , Low- $\alpha$ , and  $\theta$  average results in situation 2, situation 3, and situation 4. The blue line represents the subject's High- $\alpha$ , Low- $\alpha$ , and  $\theta$  average results in situation 1 (default awake). In the experiment, we determine whether the subject is fatigued or not with the help of attention and meditation. We also produce the relationship graph based on the average of High- $\alpha$ , Low- $\alpha$ , and  $\theta$ .

There are some dramatic differences on the y-axis maximum among these three figures. When the MindWave device couldn't detect the subject's brainwaves, the High- $\alpha$  and Low- $\alpha$  values were over 60000, and the  $\theta$  value was over 120000. In order to avoid erroneous experimental results, we deleted all of those extreme values.

Figure 3 shows that the subjects' average High- $\alpha$  value was higher while awake than in a fatigue state.

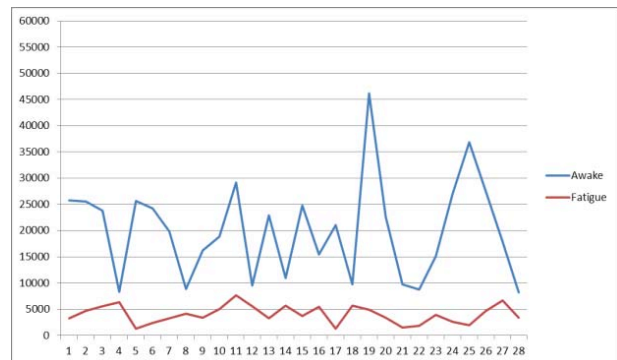


Figure 3. High- $\alpha$  Average

Figure 4 shows that the subjects' average Low- $\alpha$  value was higher while awake than in a fatigue state.

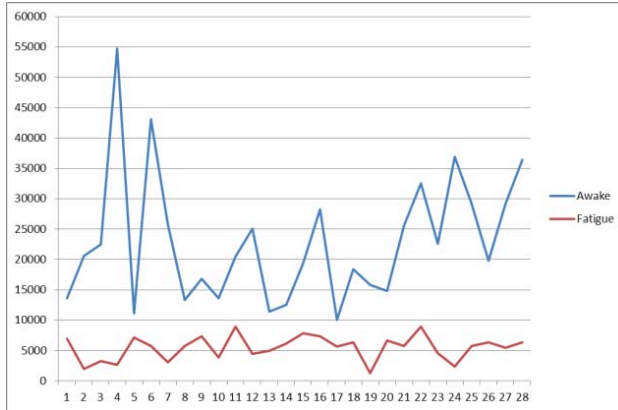


Figure 4. Low- $\alpha$  Average

In contrast to these results, Figure 5 shows that subjects' average  $\theta$  value was higher while fatigued than in a waking state.

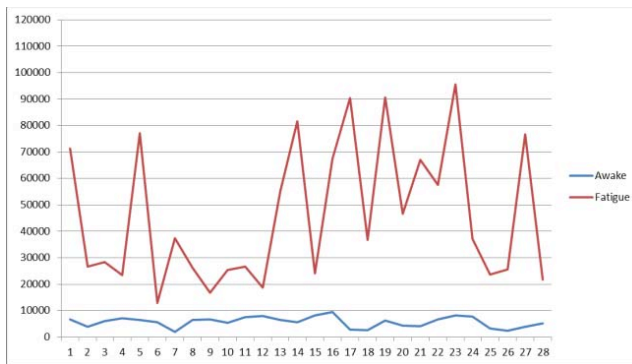


Figure 5.  $\theta$  Average

Using Fig. 3 and Fig. 4, we determined that the subject was fatigued when the average fatigue level was higher than the average waking state level. In contrast, Fig. 5 demonstrates that the subject was fatigued when the average waking state level was higher than the average fatigue level.

$$A_x = \text{situation 1 average awake} \quad (1)$$

$$B_x = (\text{situation 2 average fatigue} + \text{situation 3 average fatigue} + \text{situation 4 average fatigue})/3 \quad (2)$$

The average Low- $\alpha$ , High- $\alpha$ , and  $\theta$  values in different situations were calculated using Eq. 1 and Eq. 2. Specifically, Eq. 2 considered results from three different situations to simulate a standard for detecting an average driver's situation. In both of these equations, High- $\alpha$ , Low- $\alpha$ , and  $\theta$  can be substituted for  $x$ .

For High- $\alpha$  and Low- $\alpha$ , we found that the fatigue value was higher than the waking state value in common situations as shown in Fig. 3 and Fig. 4, so we divided the average fatigue value by average waking state value to get a marginal value to detect the driver

status. When the driver's brainwave was higher than this marginal value, we determined that the driver's fatigue level was far higher than average.

$$\text{High-}\alpha = B_x/A_x \quad (3)$$

$$\text{Low-}\alpha = B_x/A_x \quad (4)$$

As for  $\theta$ , we found that the fatigue value was higher than the waking state value in common situations as shown in Fig. 5, so we divided the average waking state value by the average fatigue value. When the driver's brainwave was lower than the marginal value, the driver was considered to be fatigued.

$$\theta = A_x/B_x \quad (5)$$

After calculating an average value for Low- $\alpha$ , High- $\alpha$ , and  $\theta$ , we excluded extreme values and those larger than 1 before finally calculating the  $X$  values of Low- $\alpha$ , High- $\alpha$ , and  $\theta$  to be 0.7, 0.5, and 0.5, respectively.

### 4.3 Performance Analysis

Before the experiment, each subject was asked to put on the MindWave device to collect their clear brainwaves for two minutes. This data was then used, as Eq. 1, as a control to compare the results against the data collected from the simulated situations that followed.

After the subject entered the application, the system began to detect EEG signals. When the system detected that the driver was in a state of fatigue for longer than 10 seconds, the system displayed a warning message, using different colors based on the degree of driver fatigue. These red, yellow, and green messages were also accompanied by different alert sounds. Red signified severe fatigue and meant that the driver was not in a suitable state for driving. The yellow message signified medium fatigue and recommended that the driver take a break. The green message indicated light fatigue, perhaps registering that the subject's blink frequency was too high, and recommended that the driver relax.

Of the 50 tests using this fatigue warning system, only 5, or about 10%, generated false alarms. The results showed that this fatigue warning system accurately predicted driver fatigue about 66.34% of the time.

Table 4. Using EEG and eSense™ to Determine Fatigue

States	Determination
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Mild fatigue (Level one)	Brainwave	Low- $\alpha < 0.7$ , High- $\alpha < 0.5$ , and $\theta > 0.5$	Brainwave choose one accord or eSense <sup>TM</sup> choose one accord
	eSense <sup>TM</sup>	30 < Attention < 40, 60 < Meditation < 80	
Medium fatigue (Level two)	Brainwave	Low- $\alpha < 0.7$ , High- $\alpha < 0.5$ , $\theta > 0.5$	Brainwave choose two accord or eSense <sup>TM</sup> choose one accord
	eSense <sup>TM</sup>	Attention < 30, 80 < Meditation	
Severe fatigue (Level three)	Brainwave	Low- $\alpha < 0.7$ , High- $\alpha < 0.5$ , $\theta > 0.5$	Brainwave is full compliance or eSense <sup>TM</sup> is full compliance
	eSense <sup>TM</sup>	Attention < 30, 80 < Meditation	

#### 4.4 GPS Positioning and Cloud Storage

As shown in Figure 6, the system will upload the driver information, including the fatigue states and the GPS location, to the cloud server in real-time while the subject is driving. After integrating and analyzing the state of the driver with the cloud server, the data is divided into light fatigue (level 1), medium fatigue (level 2), and severe fatigue (level 3).

The system is based on a mobile device locating the driver's coordinates and detecting the vehicle within a radius of twenty meters from the previous coordinates. As shown in Eq. 6, when the user is determined to be severely fatigued, the system will automatically save the user's current location, with longitude and latitude, to the server database as an alert. This system will scan for other alerts within a radius of 20 meters every 10 seconds. If there is a record in the database, the system will compare the time of the record to the current time. If the difference is less than 10 seconds, the system will alert the user that there is a fatigued driver nearby so that drivers can be more cautious. The GPS system can also alert users to drive more safety, by sending messages to fatigued drivers informing them of their current state of fatigue. In this way, the server will notify fatigued drivers and other nearby drivers of the need to be more vigilant.

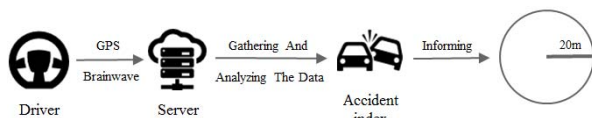


Figure 6. Cloud Storage and Analysis

$$\text{Number of vehicles}/100 \quad (6)$$

The cloud database also includes data about accident-prone roads, provided by the Department of Transportation. Once a driver's GPS location shows registers within 100 meters of one of these dangerous roads, the system will alert the driver to pay attention.

#### 4.5 Dangerous Situation Analysis

The beta-brainwave is easier to determine when a person is awake. As beta-brainwave activity increases, the human body becomes more nervous about reacting immediately to incoming situations. The energy of the brain is not only used to keep its own systems working, but also to lead the human defense system into preparation mode, which simultaneously decreases the ability of the immune system. In this situation, the human body consumes more energy than usual, leading to fatigue more quickly. If a person in this state doesn't rest enough, then the pressure will begin to increase and eventually cause adverse bodily effects leading to shutdown. The appearance of higher beta-brainwave activity demonstrates that the human body is physically tight. Since average drivers are not so nervous while navigating traffic, this could be an index marking moments when a driver encounters unexpected situations. Implementing this information into the software application, the collected data on the cloud server could be analyzed to identify areas where higher beta-brainwave activity was collected, then mark these as dangerous areas, and subsequently warn drivers.

On the other hand, we can also send messages that a driver is mentally pressured to that driver's designated contacts. As shown in Figure 7, the determining method is as the following:

1. Class-0: Determine whether the situation is a high-beta brainwave condition that last at least x seconds. By default, the value of x is 5.
2. Class-1: If the condition described in the previous step is confirmed, the situation will be rated class 1 for 30 seconds. The x-value goes to 10 and the system determines whether a high beta-brainwave condition lasts at least 10 seconds. If this is confirmed, the situation will be rated class 2; otherwise, the situation reverts to class 0.
3. Class-2: If the condition described in the previous step is confirmed, the situation will be rated class 2 for 45 seconds. The x-value goes to 15 and the system determines whether a high beta-brainwave condition lasts at least 15 seconds. If this is confirmed, a warning message will be sent to designated contacts and the situation will be rated class 3; otherwise the situation reverts to class 0.
4. Class-3: If the condition described in the previous step is confirmed, the situation will be rated class

2 for 45 seconds. The x-value goes to 15 and the system determines whether a high beta-brainwave condition lasts at least 15 seconds. If this is confirmed, the driver is determined to be nervous for a long time. The mobile device will pop out a button and voice to confirm the status of the driver. If the driver presses the button, the situation will return to class 0; otherwise the system will send the driver's location to designated contacts.

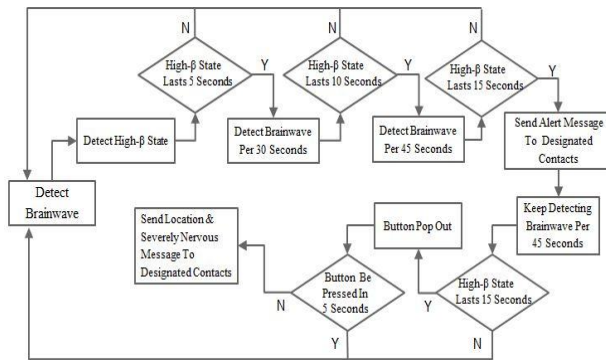


Figure 7. Using High- $\beta$  to Analyze Dangerous Situations

## 5. System Analysis

Figure 8 shows a functional flow chart of this system described in this study. The functions are as follow:

1. The system starts by asking whether the driver is a member or not. If so, then the driver is logged into the system. If not, then the system takes the driver to the registration page. The system will automatically transmit a confirmation to the user's email and reconfirm it after registration. The system will automatically detect the MindWave Bluetooth device and connect after login.
2. After login, the user will enter the home screen, which contains the following functions: fatigue warning, fatigue state statistics, user location, Bluetooth received signal strength, and set contact person.
3. Fatigue Warning: Once the system detects fatigue, a warning window will pop out with a whistle. This achieves the effect of reminding drivers of their fatigue. Drivers can use their voice to end the alarm sound and the system will go back to the home screen. If the user does not close the alarm sound within 10 seconds, the system will determine that the user is currently unfit to drive. The system will automatically record the user's current location and time, based on GPS, and send a message to the person listed in the preset contacts.

4. Fatigue state statistics: Each period of fatigue statistical data will use percentage charts and line charts. In addition to viewing a user's mental state while driving, a company can determine if a staff member is suitable to drive at this time or not.
5. User location: Tells the user which roads have a fatigue phenomenon. The system will remind users to pay attention when traveling these roads.
6. Bluetooth received signal strength: To avoid situations in which the mobile device cannot receive user EEG data, the Bluetooth signal strength is recorded to determine when the NeuroSky MindWave is too far away from the system sensor.
7. Setting contact person: If the system determines that the driver is severely fatigued, it will automatically transmit the driver's GPS location to the phone number of the person registered as a preset contact. This feature informs a driver's family or friends that the driver is currently experiencing a high risk of fatigued driving.

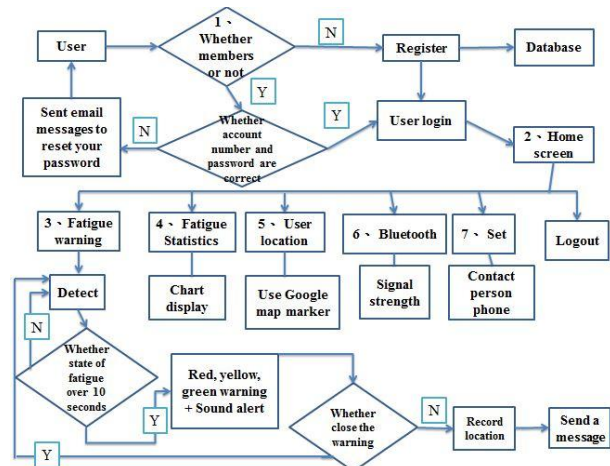


Figure 8. System Flow Chart

## 6. Discussions and Conclusion

The fatigue warning system described in this study reported driver fatigue with an average accuracy of 66.34%. This fatigue warning system was implemented with a NeuroSky MindWave headset with the capability of minimizing false alarms and providing three distinct levels of warning alerts.

Fatigue monitoring systems can be developed in many areas, making it especially useful in the management and technology sectors. Management can use this system to reduce staff burden and develop more highly efficient work policies. The system can identify employees' mental states to achieve more efficient management of those resources. In the technology sector, high-risk mechanical operators can



benefit from this system, reducing costs to the company and risk of injury to employees.

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