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REVIEW OF DRIVER FATIGUE DETECTION BY PHYSIOLOGICAL METHODS

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Abstract

Driver fatigue is one of the factors which introduces risk in transportation industry. Fatigue contributes to the increase in the number of vehicle crashes happening all over the world. Driver fatigue can be a serious problem for road safety, as tiredness can impair a driver's ability to react to road hazards and make appropriate decisions. There are technologies which identifies drowsiness of the driver by monitoring various factors and alert the driver if needed. Physiological methods are commonly used to detect driver fatigue, as they are based on changes in the body's physiological responses that occur because of fatigue. The paper reviews various driver fatigue detection methods based on physiological variables.

Keywords – driver fatigue, detection methods, physiological variables.

I. Introduction

The vast advancement in automotive research have contributed much to the implementation of systems that makes automobiles more powerful, eco-friendly, safer, and easier to operate. At the same time, the statistics regarding automotive accidents are in- creasing in an alarming rate. As per WHO, in 2020, the third leading cause for number of deaths will be road accidents (Jiménez-Pinto and Torres-Torriti, 2013). Driver's fatigue is one of the important reasons for vehicle accidents. 20% to 30% of fatal vehicle crashes are due to driver fatigue (Sigari et al., 2013). Hence alerting driver in any dangerous driving condition is essential for accident prevention. Driver alerting systems should detect the drowsiness or inattention of driver and produce certain warning so that the driver will be alerted and avoid the accident (Sontakke, 2015)

Physiological methods utilize intrusive type physiological data of the driver for analysing the state of inattention. Commonly measured variables are heart rate, muscle activity, brain activity and skin conductivity (Craye et al., 2016).

The most reliable measurement of driver fatigue is by using EEG for measuring the brain activity associated with fatigue. Breathing rate can also be utilized for detecting fatigue in drivers (Solaz et al., 2016). There are passive methods that can be utilized for identifying fatigue. The advantage of using physiological signals is that it can be collected continuously.

II. Electrocardiogram based detection method.

Electrocardiogram (ECG) is the method of recording bioelectric signals generated by heart. ECG is obtained by the sampling of bioelectrical signals sensed by various electrodes attached to the surface of the body. The raw ECG signal contains noise and hence it must be processed to obtain the required data. The raw signal is initially preprocessed followed by feature extraction to get information. The preprocessing re- moves the noise from ECG data. Feature extraction separates the information from the preprocessed data. (Luthra, 2007) (Catalano, 2002)

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The information which are significant are QRS complex (Q-R-S is the three graphical deflections seen in an ECG) and Heart Rate variability (HRV) data (HRV is the variation in time interval between heart beats). HRV data manifests the physiological condition of the user. HRV is composed of multiple frequencies. It can be divided into low frequency components and high frequency components. Ratio of low frequency to high frequency components denotes the user's drowsiness. This ratio (LF/HF) is calculated from power spectrum density (PSD)estimation using Fast Fourier Transform method. (Bonjyotsna and Roy, 2014) (Catalano, 2002) (Healey and Picard, 2005)

III. Electroencephalogram based detection method.

Electroencephalography (EEG) is a well-known method for identifying sleep- ness. EEG wave form can be of five types namely, delta, theta, alpha, beta and gamma. Presence of theta waves is an indicator of onset of sleep. (Sanei and Chambers, 2013)

Brain computer interface system (BCI) is used to create a communication channel between human brain and an external interface. A BCI system captures brain activities and convert those signals to commands for controlling an external interface. Visual Evoked Potential (VEP) is the brain activity modulation occurred after receiving visual stimulus. They are comparatively easy to detect through EEG. A typical VEP based BCI system displays flashing stimuli on a screen to induce SSVEP while the user stares on it. (Resalat and Saba, 2015) (Aboalayon et al., 2016)

In this method, white LEDs are placed in the four directions, up and down, left, and right side of the eyes. The light from the LEDs enters the visual field of the user in 45◦vertically while they are placed 10 cms away from the user. To increase the evoked potentials amplitude, duty cycle was decided as 50% with frequency 20Hz. One channel EEG is used due to the advantage of shorter processing time (Oz, Fz and ground electrode). (Resalat and Saba, 2015) (Aboalayon et al., 2016)

A data set of 5 minutes are recorded. The obtained signal is cleaned first using a band pass filter. Four temporal durations (sweep length) of 0.5s, 1s, 2s, and 3s are only considered. Each 5-minute data is divided into segments with length equal to the sweep. Feature extraction is done using FFT (Fast Fourier Transform) based and PSD (Power Spectral Density) based methods. (Feature extraction is the process to represent raw image in a reduced form for decision making such as classification) The result obtained is classified using LDA (Linear discriminant analysis) and SVM (Support Vector Machine) classifiers. (A Classification algorithm is a procedure for selecting a hypothesis from a set of alternatives that best fits a set of observations.) (Resalat and Saba, 2015)

Accuracy of each method is also calculated by comparing their ITR (Information Transfer Rate) values. As per the work, the average accuracy increases with sweep lengths. SVM classifier has higher accuracy over in a temporal window of 3s which is mostly suited for sleepiness detection. (Resalat and Saba, 2015)

IV. Breath rate-based detection method.

Breathing rate has been identified as an effective method in detecting fatigue in drivers. The breath monitoring methods can be non-invasive or invasive. The most accurate among the invasive sensors is a belt sensor. A belt sensor measures the change in the volume of abdomen which is also called as plethysmography. They can be divided into three ways namely measuring change in belt tension, change in electrical resistance and change in electrical inductance. Noninvasive method uses a camera to identify the breath rate. (Solaz et al., 2016)

As the abdomen expands and contracts, the belt which is fastened around the abdomen or chest experiences change in tension. This change in tension can be analyzed by converting it into voltage and representing as a breathing cycle. By the method of electrical resistance, sensors, which are in contact with the body measures the electrical conductivity. As the body expands and contracts, the cross-section changes, allows the measurement of abdominal movement during breathing. In electrical inductance method, an elastic belt with zig zag wire is used. This method works on the principle by which when a loop carrying current changes its area enclosed, there is a variation in magnetic field created. Breathing changes, the cross-sectional area of the body, thus changing the magnetic field generated, thus providing information about breathing cycles. (Solaz et al., 2016)

The breath cycle consists of an inhalation period followed by an exhalation period. In both periods, abdominal movements are produced. Abdominal movement speed slows down at the end of each period. The movement speed is plotted over time, in which the period corresponds to the respiration rate. Short-Time Fourier Transform is used to find the respiratory rate, taking the mean of the predominant frequencies in a time window. (Solaz et al., 2016)

VI. Impedance measurement on steering wheel-based detection method.

Human body has a certain impedance value, which varies with respect to physical and mental state. The impedance value depends on a large number of parameters; hence detection of statistically significant changes is only useful for determining the human body state. There are two methods to determine the impedance value of hu- man tissue, applying alternating current to the tissue and measuring the voltage drop or applying alternating voltage and measuring current response using a pair of electrodes. The most common method is to use a bipolar electrode which contains both current/voltage application and sensing. (Stern et al., 2001)

In this work, AD5933 integrated circuit is used for measuring bio-electrical impedance. It uses two electrode configuration. The first electrode applies a sinusoidal voltage, and the second electrode picks up the current signal. The sensed signal is processed using Fast Fourier Transform to calculate the impedance. Impedance be- tween the driver's arm to arm is measured because the palm provides sufficient area of contact. Electrodes are in the form of semicircles and are placed on the steering wheel. (Venclikova et al., 2016)

Testing of the system was done using data measured which consists of impedance for six frequency values between 25kHz and 30kHz with 1kHz step. The raw data contains values that are high because of superposition of junk data results due to the driver's palm off the steering wheel during driving conditions. A filtration was done to remove those high values by using a threshold which is double of median value. Dependencies among the data sets are tested statistically. The data analysis shows that the influence of fatigue and traffic level increases the impedance value. (Venclikova et al., 2016)

An algorithm is proposed to monitor the driver's impedance value changes. Average impedance of the driver is measured during initialization. Threshold is set as double of driver's average impedance value. If the measured value is higher than threshold and lasts more than a prescribed time, an alarm is evoked. The alarm is evoked to alert the driver about the bad contact on steering wheel or increase in body impedance that reflects fatigue, stress, and inattention. (Venclikova et al., 2016)

VI. Electrooculogram signal based detection method.

Electrooculography (EOG) is a method of recording eye movements and position that records potential differences from electrodes placed around the eyes, which is called as corneal-retinal potential. Its magnitude is of about 1mV, which is sufficiently high compared to other bio-signals. As the eye moves, the potential at the electrode becomes more positive or negative depending upon the direction of movement. (Jacko, 2009) (Krupinski and Mazurek, 2012)

In this setup of experiment, EOG signal of the user is measured. The EOG signal is a composite signal. Various features which are related to fatigue can be extracted from EOG signal. The most relevant among them are.

1. Blinks features
2. Slow eye movement features (SEM)
3. Rapid eye movement features (SEM) (Krupinski and Mazurek, 2012) (Gao et al., 2015)

Blinks features: One of the component signals that can be extracted from a composite EOG signal is blinks signal. Blinks signal occurs when the eyelid makes vertical movements. From the blinks signal, various parameters related to blinking can be calculated.

Slow eye movement features: While tracking a slowly moving object, eyes will move slowly and smoothly. These movements are called as slow eye movements. Slow eye movements can occur due to fatigue.

Rapid eye movement features: This movement corresponds to the rapid change of eye orientation. The rapid changes can be extracted from the high frequency components of the composite signal. This type of movements is also closely related to fatigue. (Gao et al., 2015) (Vidal et al., 2011)

The features extracted are combined to form a feature vector over a fixed interval. The feature vector is used to create a regression model along with PERCLOS data processed using SVM. The model thus created was used to predict the fatigue level fairly accurate. (Gao et al., 2015)

VII. Skin conductance and Oximetry pulse-based detection method.

Galvanic skin response (GSR), commonly known as skin conductance is measuring the conductance of two points of skin which is a direct indication of emotional change. GSR can be used to identify mental and physiological stress situations. GSR sensor determines the electrical conductance of the skin. The exact value for a particular emotion is not significant, but higher GSR value is noticed during intense stress situations. (Stern et al., 2001) (Healey and Picard, 2005)

Oximetry pulse (OP) measures the concentration of oxygen in blood. A pulse oximeter uses absorption of infrared and visible light in tissues to calculate the oxygen saturation of hemoglobin. The variation in absorption of infrared and red by saturated and non-saturated blood are measured and processed by a microprocessor to obtain the value. The equipment also measures the pulse rate of the user. Fatigue also contributes to the reduced oxygen saturation in drivers. The performance of driver increases if the oxygen concentration improves. (Duke and Keech, 2015) (Tremper, 1989)

In this method, GSR sensor and OP sensor were worn by the driver. The resultant signals were recorded using a Bio-feedback signal processing unit. Both the pre-driving state and post driving state were recorded. A tablet PC, which is coupled to the signal unit by bluetooth, is used for the further processing of signals. A total of eighteen features were extracted from the sensor signals. The features thus extracted are combined to form a feature matrix. The feature matrix is given as input to various neural network classifiers to detect the fatigue of the driver. (Bundele and Banerjee, 2009)

VIII. Conclusion

Physiological methods for detecting driver fatigue can be highly effective, as they are based on objective measures of the body's physiological responses. By monitoring these responses, it is possible to detect signs of fatigue before they become too severe and take steps to prevent accidents and improve road safety. Drivers can take breaks or switch drivers thereby improving road safety and reducing the risk of accidents. However, further research is needed to improve the accuracy and reliability of these methods in detecting driver fatigue in real-world driving conditions.

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