DRIVER DROWSINESS DETECTION & IDENTIFICATION OF ALCOHOLIC SYSTEM USING OPEN CV ENHANCED WITH EMBEDDED TECHNOLOGY

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***Abstract*—Drowsiness in drivers has become a serious cause of concern due to the occurrences of a large number of fatalities on the road each year. Lives of pedestrians and passengers are put to risk as drivers tend to fall asleep at the steering wheel. In the recent past, many researchers have paid attention to the problem of drowsiness detection since safe roads and safe driving are of paramount concern to all societies. This paper has led to the development of several novel and effective methods in detecting drivers' drowsiness. These include Vehicle based methods, Behavioral methods and Physiological methods. Since wake-sleep is an intermediate state between two physiologically dissimilar states, physiological signals can define this transition more accurately when compared with approaches that fall in other categories. This paper focuses on the role of physiological signals in detecting driver's drowsiness level. The proposed methods measure the physiological signals by means of various sensors, which monitor the driver's physiological parameters on a continual basis. Multiple sensors can be embedded on the driver or in the vicinity of the driver to capture vital signs indicating the onset of drowsiness. The aim here is to provide an insightful review of all such key approaches that fall in this category. This paper conducts a detailed study in which key physiological parameters that relate to drowsiness are identified, described, and analyzed. Furthermore, the overall advantages and limitations of these physiological based schemes are also highlighted.**

***Keywords*—Drowsiness, GSM Module, ECG, EEG, Fatigue.**

I. Introduction

Drowsiness can be defined as 'the propensity to fall asleep'. The transition time from awake to sleep can be categorized in three stages: fully awake, Non Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep. NREM and REM sleeps occur cyclically over the period of sleep. NREM sleep can be defined as deep but dreamless sleep. Autonomic physiological activity is found to be very low in this sleep state. NREM sleep covers 75 to 80 percent of total sleep time. NREM sleep is also known as slow-wave sleep. The remaining 20 to 25 percent period is just REM sleep. Sleep episode initializes with NREM I, lasts for 1 to 7 minutes and contributes 2 to 5 percent of total sleep. This is actually a shift from awake to sleep, also known as Sleep Onset (SO), commonly termed as drowsiness.

Driver fatigue leading to drowsiness has been identified as one of the major causes responsible for serious road fatalities. In a report of US National Highway Traffic Safety Administration, it is found those drivers' drowsiness results in 1,550 deaths, 71,000 injuries and $12.5 billion losses in revenue every year. In the state of Victoria in Australia, almost 300 injuries and 50 deaths are caused by drowsiness each year. Research that leads to the development of robust and effective drowsiness detection system is crucial to prevent impending accidents due to driver drowsiness. Various physiological activities during driving such as the activities of central nervous system from

ElectroEncephaloGram (EEG) and ElectroOculoGram (EOG), activities of autonomous nervous system from ElectroCardioGram (ECG), Skin Temperature (ST), and Galvanic Skin Response (GSR) and neuromuscular activities as ElectroMyoGram (EMG) are observed and examined to differentiate drivers' drowsiness from wakefulness. Sometimes these signals are combined together to upsurge the accuracy of the detection process. Many different technologies involving the use of novel types of electrodes have been proposed in recent past. From wet to dry electrodes, an up gradation has been observed. The widely used plating material for Biofeedback sensors is silver/silver chloride. Beside this, gold, stainless steel and a mixture of silver/silver chloride, aluminum, gold/gold chloride, nickel and titanium are being used in current sensor technologies. There are two types of bio electrodes: one is wet, which requires electrolytic gel to make the surface act as a conductor and the other is dry. Wet electrodes are appropriate for clinical applications as it causes discomfort in real world monitoring. Thus dry electrodes are widely being used in drivers' fatigue related studies.

A list of commercially available bio-sensors has been given in Table I. This paper investigates the role of the physiological measures in drowsiness detection. To the best of our knowledge we have not come across any previous work that has discussed key physiological parameters or markers such as Heart Rate Variability (HRV), and the spectral components of HRV, the EEG band components (delta, theta, alpha, beta), EEG entropy, blink amplitude and frequency, PERCLOS, SEM of EOG, EMG and GSR amplitude and ST, their association (positive/negative) to drowsiness, and the overall effectiveness of such measures as well as challenges present in the use of these schemes. The variations in physiological parameters and their effect on drowsiness, along with the overall advantages, and limitations of these schemes are discussed in detail.

II. Existing System

In the existing system, ECG and EEG sensor based Drowsiness detection is implemented and sensor are suitable in laboratory monitoring, but during driving it's not suitable and, it connected to driver body, so there is not comfort to the person during driving and the sensor value may various depend upon light intensity so it give the abnormal result.

III. Proposed System

In the proposed system, we are going to implement this project as a driver sleep detection and drunk and drive monitoring system. The camera is placed in raspberry pi to capture that the driver is in sleep mode with the help of image processing technology and the sensor are used for driver monitoring for avoid drink and drive. If it detects that the driver is in sleeping condition based on the eye closing the system capture the person and updated to server, the IOT modem is used for getting the location and updated to server. If the person drink and drive or drowsiness. The motor is continuously rotate but if it finds driver is in sleepy condition and drink and drive or accident updated to server and cutoff motor.

IV. Block Diagram

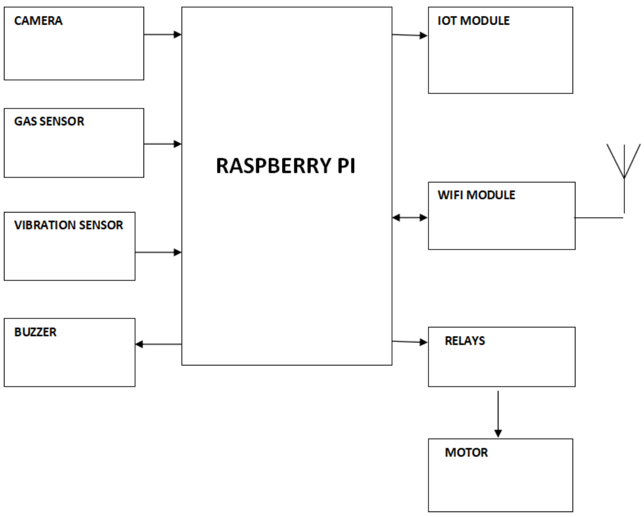

Fig.1. Block Diagram of the Proposed System

V. Block Diagram Description

In the block diagram description, 5V power supply is required for Raspberry pi 3. USB camera is connected in USB port of raspberry pi to capture the driver sleep condition. A buzzer is connected in USB port of raspberry pi 3 to get a alert sound. The gas sensor is connected to the raspberry pi for drunk and drive. A motor is connected in raspberry pi it will stop if it detects driver is in sleepy condition or drunk and drive. A IOT module is used for getting the location of the vehicle and send to server and capture image is also sensed to server

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via wifi module and 16GB SD card is connected in raspberry pi 3 which contains the raspbian OS.

VI. Working Principle

Object Detection using Haar feature-based cascade classifiers is an effective object detection method proposed by Paul Viola and Michael Jones in their paper, "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images.

Here we will work with face detection. Initially, the algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier. Then we need to extract features from it. For this, Haar features shown in the below image are used. They are just like our convolution kernel. Each feature is a single value obtained by subtracting sum of pixels under the white rectangle from sum of pixels under the black rectangle.

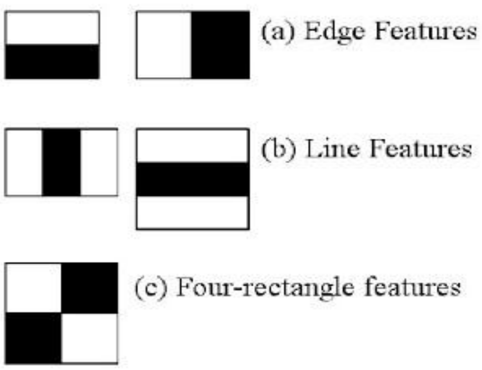

Fig.2.Examples of Haar features

Now, all possible sizes and locations of each kernel are used to calculate lots of features. (Just imagine how much computation it needs? Even a 24x24 window results over 160000 features). For each feature calculation, we need to find the sum of the pixels under white and black rectangles. To solve this, they introduced the integral image. However large your image, it reduces the calculations for a given pixel to an operation involving just four pixels. Nice, isn't it? It makes things super-fast.

But among all these features we calculated, most of them are irrelevant. For example, consider the image below. The top row shows two good features. The first feature selected seems to focus on the property that the region of the eyes is often darker than the region of the nose and cheeks. The second feature selected relies on the property that the eyes are darker than the bridge of the nose. But the same windows applied to cheeks or any other place is irrelevant. So how do we select the best features out of 160000+ features? It is achieved by Adaboost.

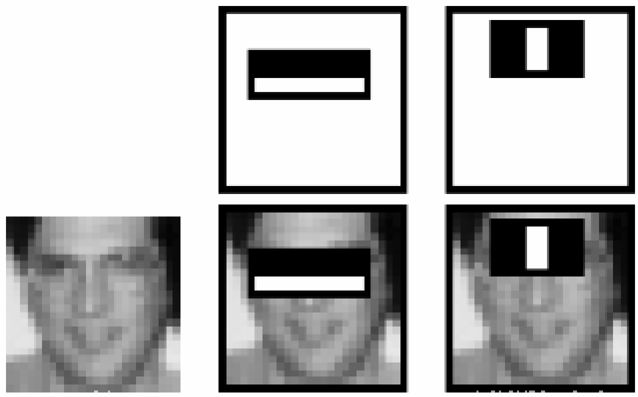

Fig .3.Working of Haar based eye detection

For this, we apply each and every feature on all the training images. For each feature, it finds the best threshold which will classify the faces to positive and negative. Obviously, there will be errors or misclassifications. We select the features with minimum error rate, which means they are the features that most accurately classify the face and non-face images. (The process is not as simple as this. Each image is given an equal weight in the beginning. After each classification, weights of misclassified images are increased. Then the same process is done. New error rates are calculated. Also new weights. The process is continued until the required accuracy or error rate is achieved or the required number of features are found).

The final classifier is a weighted sum of these weak classifiers. It is called weak because it alone can't classify the image, but together with others forms a strong classifier. The paper says even 200 features provide detection with 95% accuracy. Their final setup had around 6000 features. (Imagine a reduction from 160000+ features to 6000 features. That is a big gain).

So now you take an image. Take each 24x24 window. Apply 6000 features to it. Check if it is face or not. Wow.. Isn't it a little inefficient and time consuming? Yes, it is. The authors have a good solution for that.

In an image, most of the image is non-face region. So it is a better idea to have a simple method to check if a window is not a face region. If it is not, discard it in a single shot, and don't process it again. Instead, focus on regions where there can be a face. This way, we spend more time checking possible face regions.

For this they introduced the concept of Cascade of Classifiers. Instead of applying all 6000 features on a window, the features are grouped into different stages of classifiers and applied one-by-one. (Normally the first few stages will contain very many fewer features). If a window fails the first stage, discard it. We don't consider the remaining features on it. If it passes, apply the second stage of features and continue the process. The window which passes all stages is a face region. How is that plan!

The authors' detector had 6000+ features with 38 stages with 1, 10, 25, 25 and 50 features in the first five stages. (The two features in the above image are actually obtained as the best two features from Adaboost). According to the authors, on average 10 features out of 6000+ are evaluated per sub-window.

So this is a simple intuitive explanation of how Viola-Jones face detection works. Read the paper for more details or check out the references in the Additional Resources section.

Haar-cascade Detection in OpenCV

OpenCV comes with a trainer as well as detector. If you want to train your own classifier for any object like car, planes etc. you can use OpenCV to create one. Its full details are given here: Cascade Classifier Training.

Here we will deal with detection. OpenCV already contains many pre-trained classifiers for face, eyes, smiles, etc. Those XML files are stored in the opencv/data/haar-cascades/ folder. Let's create a face and eye detector with OpenCV.

First we need to load the required XML classifiers. Then load our input image (or video) in grayscale mode.

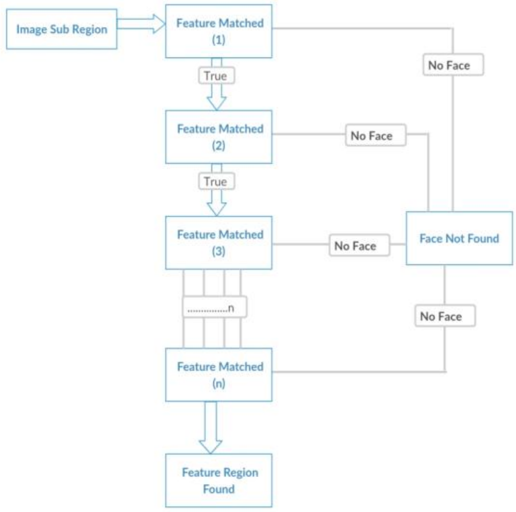

Fig. 4 . Finding face from different sub region

VII. Conclusion

The primary motive of this research is to provide a drowsiness detection system and a method that detects the driver's drowsiness in real-time. Existing approaches have used vehicle-based and psychological measurements to detect the drowsiness of the driver. However, such techniques are highly intrusive and depend on the physical characteristics of the surrounding environment. In contrast to the beforehand determined issues, we have proposed a system that implements a non-intrusive technique for determining the driver's fatigue. Our system consists of a Raspberry-Pi and a Pi camera module that continuously keeps scanning for facial landmarks. These landmarks are localized using facial landmark detector and then the eye landmarks are used to detect the eye movement. If the eye movement decreases from the threshold value and the eyes remain closed for too long then the system immediately alerts the driver with the aid of a buzzer. Furthermore, to ensure that the problem has been taken care of, a notification is sent to the owner of the vehicle through mobile when the driver dozes off for more than a couple of times. This method is useful to people in the car rental and driving business such as truckers and taxi cab drivers. However, there is one issue that remains to be addressed in the system, which is its incapability to serve its purpose at night.

VIII. Future Work

In future, we would like to improve our system by attaining a compact design and also by making it appropriate to serve under any physical environments. Apart from this, we would also like to work on recognizing the sleep pattern of the driver for detecting his fatigue level beforehand in the future. We believe, if the sleep pattern can be recognized and combined with the eye closure pattern, it is possible to form a positive correlation between these two patterns which can help us design a near perfect drowsy detection system.

IX. Results and Discussion

On completion of this work, our system could successfully detect the drowsiness of the driver based on the eye movement.

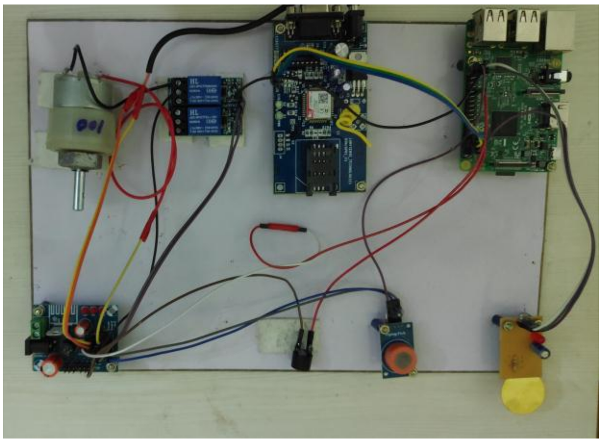

Fig . 5 .Final Prototype

X. References

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