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A non-intrusive approach for drowsy and drunk driving using computer vision techniques

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ABSTRACT

This paper presents a holistic, non-intrusive approach for drunk and drowsy detection of the driver using computer vision techniques of facial landmark detection and motion detection. The driver's continuous real-time video feed is observed with the help of a smartphone camera. A single scalar quantity, Eye Aspect Ratio (EAR) which characterizes persistent eye blinks continuously analyses this feed. Simultaneously the system checks the body and the head movements using the differential imaging technique, which operates in real-time. A severity score indicating the fitness to drive is generated cumulatively using both methods. The driver is notified with the sound of an alarm if the results are positive based on a threshold value of the severity score.

Keywords— *Computer vision, Real-time processing, Motion detection, Facial landmark detection, Eye Aspect Ratio, Severity score*

1. INTRODUCTION

Drunk and drowsy driving are the leading causes of road accidents across the world. Klauer et al. [1] have found that drowsiness increases the risk of an accident up to six times, which is further compounded due to nighttime conditions or in situations without prior sufficient sleep [2]. It is a well-known fact that the influence of alcohol is one of the major causes of reduced vehicular control and increased risk of accidents. Numerous studies have established that the risks of road accidents, injury or death increase exponentially under the influence of alcohol [3]. In Europe itself, there is an estimation of 10,000 deaths each year because of drunk driving [4]. Alcohol-impaired driving accidents contribute to approximately 31% of all traffic casualties in the USA [5]. In China, Li et al. found that about 34.1% of all road accidents were alcohol-related [6]. All of these studies indicate serious human lapses and avoidable causes of death, which can be prevented by proper monitoring and alerting technology. Therefore, it is essential to develop a holistic, non-intrusive system to continuously monitor a person’s physical and facial movements and to alert them at critical moments to avoid road [17] and [18]; techniques using a stereo camera [18] and [19]. Some of these techniques have also been converted into commercial products such as Smart Eye [18], Seeing Machines DSS [19], Smart Eye Pro [18] and Seeing Machines Face API [19]. However, these commercial products are still limited to controlled environments and require laborious calibration techniques. Thus, there is a long way to go before a reliable and robust commercial product is built in this category.

The existing systems based on real-time driver monitoring, using image processing techniques are largely tackling one aspect of the problem, i.e. either drowsiness or drunkenness. To accidents, thereby significantly preventing serious injury and loss of lives.

2. RELATED WORK

Existing methods use both active and passive techniques to develop real-time monitoring systems. Active methods use special hardware such as illuminators [7], infrared cameras, wearable glasses with special close-up cameras observing the eyes [8], electrodes attached to the driver's body to monitor biomedical signals, like cerebral, muscular and cardiovascular activity [9] [10]. These methods provide reliable and accurate detection. However, the cost of such specialized equipment is a major drawback hindering their popularity. These equipment are also intrusive that is, it causes annoyance to the driver's body and hinders regular driving. The unusual effect of driving in the presence of invasive instrumentation reduces the drowsiness in testing and simulation conditions. Consequently, the efficacy of such models is limited in real road conditions. Most of them are yet to be effectively introduced in the market.

Passive techniques in monitoring systems majorly rely on the standard remote camera. A set of these passive methods are based on the driver's performance, by evaluating variations in the lateral position of the vehicle, velocity and steering wheel angle [11] [12]. The process of signal acquisition is easy and meaningful in these approaches, which has led to the penetration of these techniques into the market. However, these systems are subjected to several constraints such as vehicle type, driver's experience and condition of the road. These systems also require a considerable amount of time to analyze driver behaviours and therefore, are not suitable for critical alert systems.

Another category of passive methods is based on real-time visual analysis of the driver, using image processing techniques. Computer vision can be a natural, non-intrusive and intuitive solution for monitoring drowsiness and loss of vehicle control due to stupor under the influence of alcohol. These approaches are both cost-effective and efficient, as the indications of drowsiness and drunkenness can be easily detected through facial and head/body movements. Several analysis algorithms and cameras have been documented in the literature for this approach: techniques using visible spectrum camera [13] and [14]; methods using an IR camera [15], [16], the best of the authors' knowledge, there are no software solutions using image processing techniques, for tackling both these problems as a whole and providing a complete analysis of whether the driver is fit to drive or not. The present approach requires no sophisticated or costly hardware equipment or difficult calibration processes and is simple, user-friendly and cost-effective. The solution is completely non-intrusive and does not hinder or influence the driving process in any manner. The techniques of facial landmark detection and motion detection using differential images are computed in real- time with negligible computational costs, ensuring quick response and alert at critical moments to avoid unfortunate accidents. This paper presents a two-pronged approach for holistic driving fitness detection, checking for both drowsiness and the potential influence of alcohol, using computer vision techniques of facial landmark detection and motion detection, using a simple smartphone camera installed in the vehicle, which leads to significantly enhanced probabilities of avoidance of road accidents, injury and death.

3. PROPOSED WORK

The proposed work targets both the detection of drowsiness and reduced vehicular control due to stupor induced by the influence of alcohol and even sleep deprivation, simultaneously and provides a solution which detects and reports such conditions in real-time.

The main system flow diagram is shown in Fig. 1. The input to the system is a video feed captured by a simple smartphone camera attached in a position to get a continuous video feed of the head and upper body of the driver. This feed is processed frame by frame, by the system. Drowsiness is detected by the blink patterns of the eyes, using facial landmark detectors [20], which provide a precise method for estimation of eye-opening using a single scalar metric called Eye Aspect Ratio (EAR). Simultaneously, an analysis to detect head and body movements of the driver is performed, to ascertain whether he/she is potentially under the influence of alcohol or sleepy or both. The relative lateral movement determines the head tilt angle. When the head angle goes beyond a certain threshold, the unusual behaviour of the driver is recorded. The results of both of these analyses are combined to yield a cumulative severity score. Based on this score, the system sounds an alarm, implemented via a voice notification output, to alert the driver and for moderate to high severity conditions, the location of the smartphone is sent to the respective kin and concerned authority. Location of the smartphone is sent to the respective kin and concerned authority.

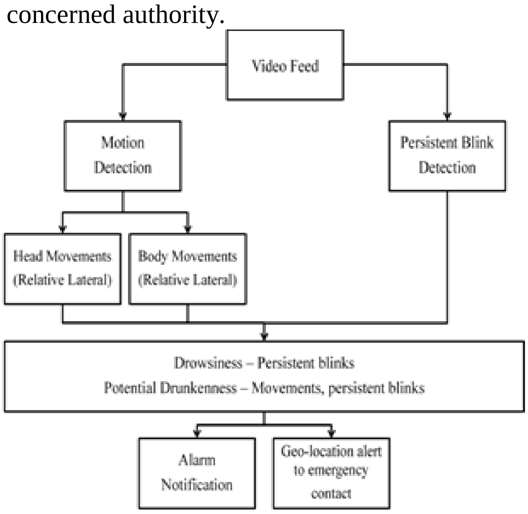

Fig. 1: Driving fitness detection- system flow diagram

3.1 Real-time eye blink detection

Observation of the eyes and measurement of eye closure is an accurate measure of drowsiness detection. If the distance between the eyelids is tending to zero, then a blink is detected. If this value persists beyond a certain period of time, known as the blink threshold, then it can be said that the driver is drowsy.

The process of finding the location of different facial features such as the eyes, eyebrows, mouth etc. accurately, using shape prediction methods, is called facial landmark detection. We propose to identify the facial landmarks to locate the eyes and eyelid contours. We use the Dlib [23] 68 point land marking model, because of its ability to detect facial landmarks in real-time, with high-quality predictions and greater accuracy over the 5 point land marking model, all of which are critical factors for our application. This pre-trained facial landmark detector, as a part of the Dlib library, has 68 (x, y) coordinates which map to the facial structures or landmarks of the face. Out of these landmarks, the left and right eyes are of interest to us, both of which are characterized by 6 (x, y) coordinates. These are shown in figure 2. The coordinates are numbered starting from the left corner of the eyes and working clockwise around it.

From these landmarks detected, a scalar quantity called the Eye Aspect Ratio (EAR) is calculated to estimate the openness of the eye. This ratio is calculated as an average for both the eyes and monitored over a series of 48 frames so that the presence of a persistent blink is detected and an accurate result is obtained.

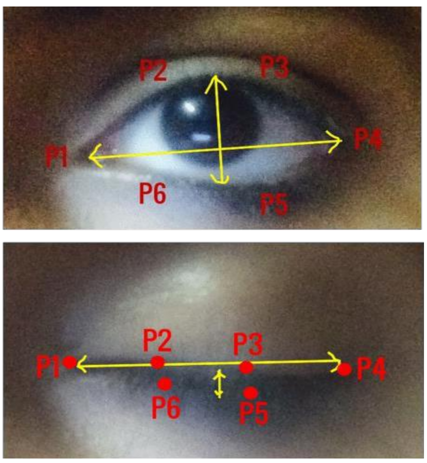

Fig. 2: Eye landmarking in an open and closed eye

The EAR is calculated as the Euclidean distance between the height and width of the eye as

$$\text{EAR} = (|p2\text{-}p6|+|p3\text{-}p5|)/(2*|p1\text{-}p4|) \quad (1)$$

Where p1, p2, … , p6 are the coordinates in the 2D landmark locations, shown in figure 2.

For the open eye, the EAR is almost a constant value, whereas it rapidly tends to zero for a closed eye. When the value of EAR drops below a threshold called the Eye Aspect Ratio (EAR) threshold, a blinking state of the eye is detected. In order to obtain an accurate and organic value for the EAR threshold suitable for our application, we chose a random sample set of subjects and computed the EAR under the variation of a multitude of attributes: lighting conditions including dim and bright lighting and flickering between both; height of the subject and the relative elevation from the camera; the eye shape and size of the subject; the presence and absence of spectacles. After computing these values, we have found the optimum value of the blink threshold for accurate detection of drowsiness, to be 0.3.

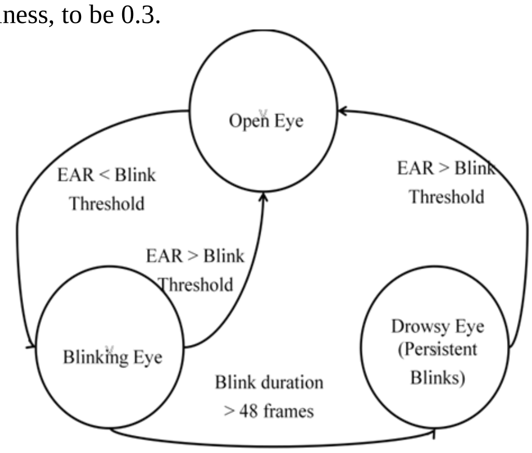

Fig. 3: Eye blink detection state machine diagram

Sounding an alert at this stage would be erroneous and would lead to multiple false alarms. Our system monitors the EAR for a consecutive period of 48 frames, to check if the value drops further and does not increase, indicating a state of persistent blinks.

In case of a positive result, the algorithm returns a Boolean flag, called the drowsiness flag (D), marking drowsiness detection as true. This flag is further used in severity score calculation and yielding alert results. The state machine diagram of real-time blink eye detection is shown in Fig. 3. The advantage of using the scalar EAR value for drowsiness detection ensures real-time detection of drowsiness since the computation cost of the EAR metric from facial landmarks is almost negligible. Thus, critical moments of drowsiness can be detected and reported with almost negligible response time.

3.2 Motion detection using differential images technique

While driving, the driver should be in a state of complete alertness and concentrate fully on the road. But in a state of drowsiness or under the influence of alcohol, the driver loses their consciousness and finds it difficult to maintain a steady position of their hands and body. Our system monitors these motions of the driver using the differential images technique of motion detection. Our current approach focuses on relative lateral movements of the head and upper body, as the relative transverse movements are difficult to detect through the successive series of frames. If lateral movements relative to the driver's usual mean position are present in a series of consecutive frames and exceed a specified angular threshold, then it can be concluded that the driver is losing control of the vehicle, potentially under the influence of alcohol or drowsiness or both.

The proposed algorithm converts the video stream into an image array, in order to facilitate a comparison in the difference in positions, which enables the system to detect motion. The images are then resized to a uniform size and converted into grayscale.

Subtraction of two images pixel by pixel yields a differential image, which enables the system to clearly identify any relative movement which may have taken place in the consecutive frames. The calculation of a differential image is done as follows:

$$g_{diff}(x, y) = g_1(x, y) - g_2(x, y) \quad (2)$$

Where, g(x, y) is the image function for the (x, y) coordinates for each pixel in the image.

Our approach considers three consecutive image frames at any particular instance, the current image frame, the previous image frame and the next image frame.

These can be labelled as:
It-1: Image at time t - 1, i.e. the previous image frame
It: Image at time t, i.e. the current image frame
It+1: Image at time t + 1, the next image frame

Two differential images, ΔI1 and ΔI2 are calculated. ΔI1 denotes the differential image between the current and next image frame, whereas ΔI2 denotes the differential image between the current and previous image frame. The final differential image ΔI is a bitwise AND operation between the two differential images. Performing a bitwise AND operation on two images is a commonly used technique to extract a particular part of the image. In the present case, the head and body of the driver are extracted separately from the static background. The differential images are grayscale images, with a single colour channel. Bitwise AND operations are performed on these colour channel values for each pixel of the two differential images under consideration. This is an inbuilt function available in the OpenCV [21] library, which has been used to implement this algorithm. The approach can be summarized as below:

$$\Delta I1 = It{+}1 - It \quad (3)$$
$$\Delta I2 = It - It{-}1 \quad (4)$$
$$\Delta I = \Delta I1 \wedge \Delta I2 \quad (5)$$

Considering differential images between three consecutive frames removes the unnecessary background of the images under consideration, and yields accurate results with regard to relative motion between the frames. During our laboratory investigation of this method, it has been found to be efficient in removal of both static and dynamic backgrounds, since the differential images are a representation of the gradual changes between the frames and only the relative motion of the driver is being taken into consideration. This technique also works well for both dimly and brightly lit conditions. However, the effects of a sudden drastic change in lighting remain to be investigated.

The experimental results of motion detection by differential images technique is shown in figure 4. These images are set in laboratory conditions with moderately bright lighting. The frames shown are sampled at an interval of fifteen frames, in order to clearly demonstrate the lateral head and body movement of the driver. However, the system calculates differential images from three consecutive frames. In each set of results, the images correspond to the previous frame It-1, the current frame it, the next frame It+1 and the final differential image ΔI. The corresponding value of ΔI is printed on the next line.

It can be clearly seen that the static background is successfully eliminated using this technique and only the relative motion between the frames is captured in the final differential image. The numeric value of ΔI is seen to increase significantly with an increase in lateral displacement of the head and body.

When the value of ΔI exceeds a specific threshold, known as the Differential Angular Threshold, and persists for several consecutive frames, the algorithm detects a loss of control of bodily movements due to drowsiness or drunkenness or both. The random sample set of subjects used to compute the optimum value of the blink threshold were also involved in the experiments done to compute the optimum value of the Differential Angular Threshold.

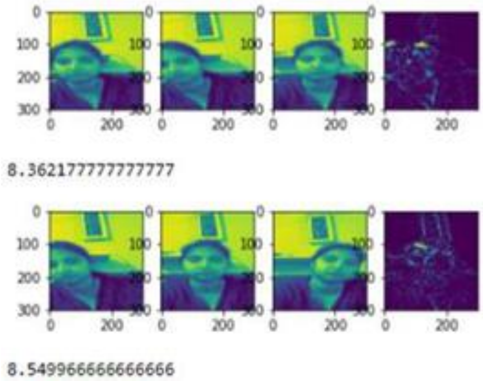

Fig. 4: Motion detection using differential images technique

In this set of experiments, the attributes which were varied are the height and build of the subject, lighting conditions and deliberate movements. The result of these experiments found that the optimum Differential Angular Threshold for the accurate detection for lateral relative motion is 2.5. Any value of ΔI more than this is flagged true for detection of motion. The corresponding Boolean flag, called the motion flag (M), is marked true and the final differential image value is returned for severity score calculation.

The usage of differential images technique for the present approach ensures its efficacy across all individual driving styles, by checking the relative lateral movement from the driver's usual mean position and monitoring this relative angular displacement for persistence over several consecutive frames. This ensures accurate results of lateral motion detection irrespective of individual styles and driving conditions.

This technique also requires almost negligible computation time and assures real-time detection of critical moments of potential loss of vehicle control and real-time reporting and alert of the same.

3.3 Alert sound and location notification

This part of the system analyzes the results of the drowsiness detection and motion detection stages and forms a cumulative severity score, which denotes the severity of the situation. This is used to ascertain the appropriate alert notification to be sent out.

Our system uses two flags, the drowsiness flag and the motion flag, to record the results of the drowsiness and motion detection analyses respectively. The conditions under which the alert needs to be sent by the system, are determined by an alert matrix, as shown in table 1.

The alert results are based on the values of the drowsiness and motion flags. If either of the flags is true, then an alert is yielded by the system.

Table 1: Alert matrix

Drowsiness Flag (D)	Motion Flag (M)	Alert Result
True	True	True
True	False	True
False	True	True
False	False	False

An alert comprises of two types of notifications, namely a voice notification or alarm, which alerts the driver and helps him/her regain their consciousness, and a geographical location notification, which is sent to the respective kin or emergency contact of the driver and/or concerned authorities, with a description of the smartphone, and consequently the driver's location, and their current critical condition.

The choice between these two types of alerts is made with the help of the severity score, calculated with the help of the following equation.

$$Severity\ Score\ (S) = \alpha * \Delta D + \beta * \Delta M \qquad (6)$$

Where, α: Weight of drowsiness factor, ΔD: Drowsiness factor β: Weight of motion factor ΔM: Motion factor.

The drowsiness factor ΔD is a numeric measure of the persistent blinks detected by the system. It is computed as the absolute difference between the value of the EAR metric at the time of persistent blink detection and the constant blink detection, that is:

$$\Delta D = |\ EAR - Blink\ Threshold\ | \qquad (7)$$

Similarly, the motion factor ΔM is a numeric measure of the deviation from the Differential Angular Threshold. It is the absolute difference between the value of ΔI and the Differential Angular Threshold, that is:

$$\Delta M = |\ \Delta I - Differential\ Angular\ Threshold\ | \qquad (8)$$

Thus, the severity score S is a weighted sum of these two factors. The weights assigned to these factors are a numeric indicator of their priorities. Since the detection of persistent eye blinks is essential for the detection of both drowsiness and the potential influence of alcohol, thus the weight (α) assigned to ΔD is greater than the weight (β) assigned to ΔM. We have found that the values of α = 2 and β = 1 work satisfactorily in the calculation of severity score and determining the alert result.

Table 2 shows the relationship between the range of severity scores and the corresponding alert yielded by the system

Table 2: Relationship between severity score range and alert yielded

Severity score range	Possible critical conditions	Alert yielded
Low	Mild Drowsiness	Voice alarm
Moderate	Drowsiness, the mild influence of alcohol	Voice alarm, geo location notification to emergency contact

Moderate Persistent	Moderate to severe drowsiness, moderate to the severe influence of alcohol or both	Persistent voice alarm, geo-location notification to emergency contact
Severe	Severe drowsiness and/or drunkenness or both	Persistent voice alarm, geo-location notification to emergency contact and concerned authorities

The geographical location of the smartphone is captured with the help of its IP address. The voice alert is sounded continuously until the driver returns back to a state of normalcy and regains control over the vehicle or manually turns it off.

The system responds to critical situations of drowsiness and potential loss of vehicle control under the influence of alcohol or drowsiness or both, in real-time, due to negligible computational times of both the real-time blink detection and motion detection modules. The alerts are also sounded almost instantly, ensuring accurate and timely alerts to prevent any unfortunate accidents.

4. IMPLEMENTATION DETAILS

The proposed system is implemented in Python 3.5 with the help of OpenCV[24] libraries, using the observer design pattern[25]. This software design pattern is used to solve problems where a one-to-many dependency is defined between objects, such that when one object changes state an open-ended number of objects dependent upon it can be notified immediately. This solution is proposed by defining a subject or an observable class, with which any number of observers can register. The registered dependent observers are notified and updated automatically when there is a change of the observable class.

The flow diagram for the system implementation is shown in figure 5.

The video stream generated by the smartphone camera is constantly monitored by an observable class called Stream Capture. The classes which implement drowsiness detection and motion detection are the dependent classes on this stream and register as observers with the Stream Capture class. When the video camera is successfully detected and the stream read, the registered observers are notified.

Similar to the Stream Capture class, a Notifier class manages the notification module in case of any drowsiness or motion detection. This is designed as an observable class with the classes implementing the alarm action and the geo-location notification action being the registered observers. Whenever the detection algorithms send any request for notifying the driver, along with the corresponding parameters, the Notifier class updates the observers and sends them a list of classes which have requested to send a notification and their corresponding parameters. The alarm action and/or geo-location action are executed according to the severity score computed by the Notifier and the control returns back to Stream Capture and the process continues.

The final product made available to the user is in the form of a smartphone application, to be installed on the driver's phone and utilizing resources like the smartphone camera, speakers and the phone's Internet connection. This ensures an easy-to-use and widely accessible application.

5. CONCLUSION AND FUTURE WORK

In this paper, we have described a holistic, non-intrusive approach to driving fitness detection, by checking for drowsiness and the loss of vehicle control under the potential influence of alcohol, based on driver visual monitoring, using computer vision techniques of facial landmark detection and motion detection using differential images.

We have also demonstrated that real-time frame based facial landmarks and body motion detectors are precise indicators for estimation of drowsiness and potential drunkenness. These are powerful measures, even for low image resolution and in-the-wild circumstances such as bad illumination, facial expressions, non-frontality etc. The computational cost for the Eye Aspect Ratio of the eye blink and detection of lateral relative motion is found to be negligible, which allows the system to send out alerts in critical situations with rapid response times.

However, the following limitations exist and can be further improved through future discussion and further work.

- We see a limitation in the assumption of a constant blink duration. However, this duration differs from person to person. An adaptive approach can yield better results.
- Nighttime and poor lighting conditions can also potentially impact the performance of real-time blink detection and motion detection algorithms. The usage of approaches which are sensitive and responsive to such conditions can further enhance the system performance.
- Another limitation to this solution is that EAR is estimated for 2D frames which is insensitive to the angle of head orientation. This solution could be further enhanced by defining a 3D EAR, using landmark detectors which estimate a 3D model of the eye landmarks in an image.
- The sending of a geo-location notification to the emergency contact of the driver, their kin or the concerned authorities introduce a requirement of an Internet connection for the system. Apart from this module, the system can function perfectly offline. The introduction of this dependency could be a subject for future discussion, as there could be possible limitations to the proper functioning of this feature in regions of poor connectivity. However, the alarm feature will work even in such situations.

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