Operator's Behavior Detection And Control System In Vehicle

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Abstract- *Drowsiness and Fatigue of drivers are amongst the significant causes of road accidents. Every year, they increase the amounts of deaths and fatalities injuries globally. In this paper, a module for Advanced Driver Assistance System (ADAS) is presented to reduce the number of accidents due to drivers fatigue and hence increase the transportation safety; this system deals with automatic driver drowsiness detection based on visual information and Artificial Intelligence. We propose an algorithm to locate, track, and analyze both the drivers face and eyes to measure PERCLOS, a scientifically supported measure of drowsiness associated with slow eye closure. In this paper, a novel approach towards real-time drowsiness detection is proposed. This approach is based on a deep learning method that can be implemented on applications with high accuracy. The main contribution of this work is the compression of heavy baseline model to a lightweight model. Moreover, minimal network structure is designed based on facial landmark key point detection to recognize whether the driver is drowsy. The proposed model is able to achieve an accuracy of more than 80%.*

Keywords- Drowsiness detection, ADAS, Face Detection and Tracking, Eyes Detection and Tracking, Eye state, PERCLOS.

I. INTRODUCTION

human activities. We all can be victim of drowsiness while driving, simply after too short night sleep, altered physical condition or during long journeys. The sensation of sleep reduces the driver's level of vigilance producing dangerous situations and increases the probability of an occurrence of accidents. Driver drowsiness and fatigue are among the important causes of road accidents. Every year, they increase the number of deaths and fatalities injuries globally.

In this context, it is important to use new technologies to design and build systems that are able to monitor drivers and to measure their level of attention during the entire process of driving. In this paper, a module for ADAS (Advanced driver assistance System) is presented in order to reduce the number of accidents caused by driver fatigue and thus improve road safety. This system treats the automatic detection of driver drowsiness based on visual information and artificial intelligence [1]. The development of drowsiness detection technologies is both an industrial and academic challenge. In the automotive industry, Volvo developed the Driver Alert Control which warns drivers suspected of drowsy driving by using a vehicle-mounted camera connected to its lane departure warning system (LDWS). Following a similar vein, an Attention Assist System has been developed and introduced by Mercedes-Benz that collects data drawn from a driver's driving patterns incessantly ascertains if the obtained information correlates with the steering movement and the driving circumstance at hand. The driver drowsiness detection system, supplied by Bosch, takes decisions based on data derived from the sensor stationed at the steering, the vehicles' driving velocity, turn signal use, and the lane assist camera mounted at the front of the car [2].

Notably, the use of these safety systems which detect drowsiness is not widespread and is uncommon among drivers because they are usually available in luxury vehicles. An increased embedding and connecting of smart devices equipped with sensors and mobile operating systems like Android, which has the largest installed operating system in cars, was shown by surveys in 20152. In addition, machine learning has made groundbreaking advances in recent years, especially in the area of deep learning. Thus, the use of these new technologies and methodologies can be an effective way to not only increase the efficiencies of the existing real-time driver drowsiness detection system but also provide a tool that can be widely used by drivers.

We propose an algorithm to locate, track and analyze both the driver face and eyes to measure PERCLOS (percentage of eye closure). The remainder of this paper is organized as follows, Section 2 presents the related works, Section 3 presents the proposed system and the implementation of each block of the system, the experimental results are shown in section 4 and in the last section conclusions and perspectives are presented.

II. LITERATURE REVIEW

In a bid to increase accurateness and accelerate drowsiness detection, several approaches have been proposed. This section attempts to summarize previous methods and approaches to drowsiness detection. The first previously-used approach is based on driving patterns, and it is highly dependent on vehicle characteristics, road conditions, and driving skills [3]. To calculate driving pattern, deviation from a lateral or lane position or steering wheel movement should be calculated. While driving, it is necessary to perform micro adjustments to the steering wheel to keep the car in a lane. Krajewski et al.[4] detected drowsiness with 86% accuracy on the basis of correlations between micro adjustments and drowsiness. Also, it is possible to use deviation in a lane position to identify a driving pattern. In this case, the car's position respective to a given lane is monitored, and the deviation is analyzed [5]. Nevertheless, techniques based on the driving pattern are highly dependent on vehicle characteristics, road conditions, and driving skills. The second class of techniques employs data acquired from physiological sensors, such as Electrooculography (EOG), Electrocardiogram (ECG) and Electroencephalogram (EEG) data. EEG signals provide information about the brain's activity. The three primary signals to measure driver's drowsiness are theta, delta, and alpha signals. Theta and delta signals spike when a driver is drowsy, while alpha signals rise slightly. According to Mardi et al.[6], this technique is the most accurate method, with an accuracy rate of over 90%. Nevertheless, the main disadvantage of this method is its intrusiveness. It requires many sensors to be attached to the driver's body, which could be uncomfortable. On the other hand, non-intrusive methods for bio-signals are much less precise.

The last technique is Computer Vision, based on facial feature extraction. It uses behaviors such as gaze or facial expression, yawning duration, head movement, and eye closure. Danisman et al.[7] measured drowsiness of three levels through the distance between eyelids. This calculation considered the number of blinks per minute, assuming that it increases as the driver becomes drowsier. In Hariri et al.[8] the drowsiness measurements are the behaviors of the mouth and yawning. The modified Viola-Jones9 object detection algorithm was employed for face and mouth detection.

Recently, the deep learning approaches, especially the Convolutional Neural Networks (CNNs) methods, has gained prominence in resolving challenging classifications problems. Most of them represent a breakthrough for various Computer Vision tasks, including scene segmentation, emotion recognition, object detection, image classification 9,10, etc. With adapted shallow CNNs, Dwivedi et al.11 achieved 78% accuracy of detecting drowsy drivers. Park et al.12 developed a new architecture employing three networks. The first one13 uses AlexNet consisting of three Fully-Connected (FC) layers and five CNNs to reveal the image feature. Furthermore, 16-layered VGG-FaceNet14 is used to extract facial features in the second network. FlowImageNet15 is used for extracting behavior features in the third network. This approach achieved 73% accuracy. Dwivedi et al.11 and Park et al.12 attempt to improve the accuracy of drowsiness detection accuracy using binary classification. Convolutional Neural Networks (CNNs) methods have largely produced an outlandish performance in the drowsiness detecting area and are also a powerful aid to various classification tasks. Installing these algorithms to practical applications on embedded systems is still burdensome since the model size is generally large and requires a high level of computational complexity.

III. SYSTEM DESIGN

In this section, we discuss our presented system which detects driver drowsiness. The overall flowchart of our system is shown in Figure 1.

3.1 Face Detection

The symmetry is one of the most important facial features. We modeled the symmetry in a digital image by a one-dimensional signal (accumulator vector) with a size equal the width of the image, which gives us the value corresponding to the position of the vertical axis of symmetry of objects in the image. The traditional principle to calculate the signal of symmetry is for each two white pixels which are on the same line we increment the value in the medium between these two pixels in the accumulator vector. (The algorithm is applied on an edge image, we called a white pixel: the pixel with value 1).

We introduce improvements on the calculation algorithm of symmetry into an image to adapt it to the detection of face, by applying a set of rules to provide a better calculation of symmetry of the face. Instead of computing the symmetry between two white pixels in the image, it is calculated between two windows (Z1 and Z2) (Figure 1).

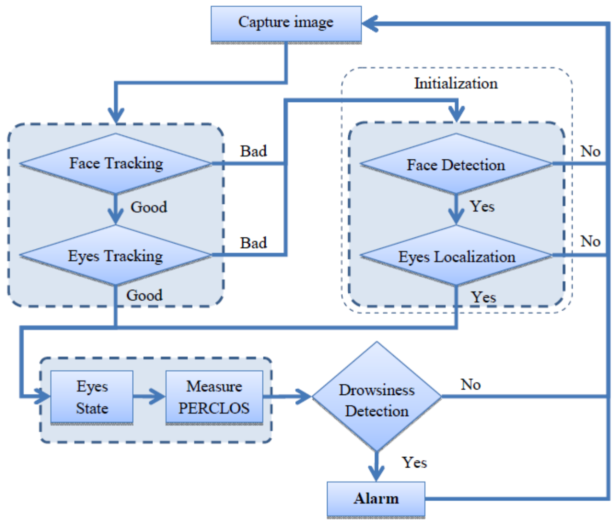

Figure 1 : Flowchart of the proposed system.

For each window Z1, we sweep the window Z2 in the area determined by the parameters S_min, S_max, and H. We increment the signal of symmetry between these two windows if the sum of white pixels is located between two thresholds S1 (maximum) and S2 (minimum). Then we extract the vertical region of the image contours (Region of Interest ROI) corresponding to the maximum index of the obtained signal of symmetry.

Next, we take a rectangle with an estimated size of face (Because the camera is fixed and the driver moves in a limited zone so we can estimate the size of the face using the camera focal length after the step of camera calibration) and we scan the ROI by searching the region that contains the maximum energy corresponding to the face (Figure 3).

We propose a checking on two axes: the position variance of the face detected according to time; i.e., in several successive images, it is necessary that the variance of the positions of the detected face is limited; because the speed of movement of the face is limited of some pixels from a frame to another frame which follows.

3.2. Eyes Localization

Since the eyes are always in a defined area in the face (facial anthropometric properties), we limit our research in the area between the forehead and the mouth (Eye Region of Interest 'eROI') (Figure 4). We benefit from the symmetrical characteristic of the eyes to detect them in the face. First, we sweep vertically the eROI by a rectangular mask with an estimated height of height of the eye and a width equal to the width of the face, and we calculate the symmetry. The eye area corresponds to the position which has a high measurement of symmetry. Then, in this obtained region, we calculate the symmetry again in both left and right sides. The highest value corresponds to the center of the eye. The result is shown in Figure 4.

3.3. Tracking

The tracking is done by Template Matching using the SAD Algorithm (Sum of Absolute Differences).

IV. RESULT AND DISCUSSION

To validate our system (Figure 2), we test on several drivers in the car with real driving conditions. We use an IR camera with infrared lighting system operates automatically under the conditions of reduced luminosity and night even in total darkness. The results of the eye states are illustrated in Table1, where the percentage error is the number of frames that have a false state of eye divided by the total number of frames multiplied by 100.

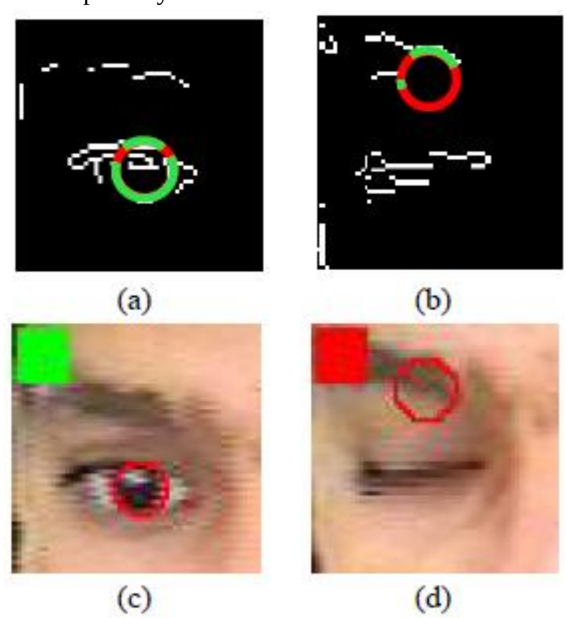

Figure 2 – Eyes states using HTC. (a) and (b) Edge detection , (c) and (d) Eyes states results.

Figure 3 yawning detection

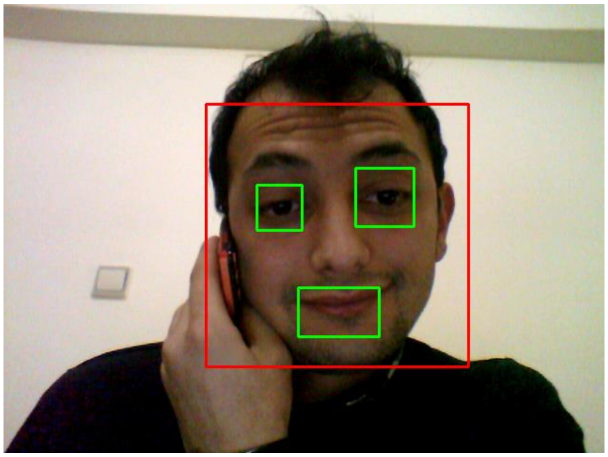

Figure 4 eye and yawning detection

The application works even in the tilted position while driving to the extent of 45 degrees so it can be real time even during the driving conditions. Face tilted has to be detected because the drivers are not going to stay in ideal condition while driving. There will be a motion in driving and it has to ready to go along with the roadbecause little vibrations. The up-ward and down-ward movement of face will be detected. Ifin-case there some drivers lean down for up while feeling drowsy. The possibilities of feeling in those directions are more. More chances of accidents occur at that situation. According to the obtained results, our system can determine the eye states with a high rate of correct decision.

V. CONCLUSION

In this paper, we presented the conception and implementation of a system for detecting driver drowsiness based on vision that aims to warn the driver if he is in drowsy state. This system is able to determine the driver state under real day and night conditions using IR camera. Face and eyes detection are implemented based on symmetry. Hough Transform for Circles is used for the decision of the eyes states.

The results are satisfactory with an opportunity for improvement in face detection using other techniques concerning the calculation of symmetry. Moreover, we will implement our algorithm on a DSP (Digital Signal Processor) to create an autonomous system working in real time.

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