IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 6, June 2021

DOI 10.17148/IJARCCE.2021.10632

Drowsiness detection system

Nagaraju Karthik[1], Koduri Pradeep Kumar[2], Mettu Likith Raghava[3], Kancherla Mahesh[4]

Guided by: **Asst.Prof.M.Ambarisha**

Department of computer science and engineering, KKR & KSR Institute of Technology & Sciences,

Guntur, Andhra Pradesh, India

ABSTRACT: In the present study, a vehicle driver drowsiness warning or alertness system using image processing technique with fuzzy logic inference is developed ,but the processing speed on hardware is main constrained of this technique. The principle of the proposed system in this paper using OpenCV (Open Source Computer Vision) library is based on the real time facial images analysis for warning the driver of drowsiness or in attention to prevent traffic accidents. The facial images of driver are taken by a camera which is installed on the dashboard in front of the driver. An algorithm and an inference are proposed to determine the level of fatigue by measuring the eyelid blinking duration and face detection to track the eyes, and warn the driver accordingly. If the eyes are found closed for 5 or 8 consecutive frames, the system draws the conclusion that the driver is falling asleep and issues a warning signal. The system is also able to detect when the eyes cannot be found. Present paper gives the overview of the different techniques for detecting drowsy driver and significance of the problem, face detection techniques, drowsiness detection system structure, system flowchart, introduction to OpenCV. The proposed system may be evaluated for the effect of drowsiness warning under various operation conditions. We are trying to obtain the experimental results, which will propose the expert system, to work out effectively for increasing safety in driving. The detail of image processing technique and the characteristic also been studied.

INTRODUCTION

Due to the increase in the amount of automobile in recent years, problems created by accidents have become more complex as well. The official investigation reports of traffic accidents point out those dangerous driving behaviours, such as drunk and drowsy driving, have taken a high proportion among all the accidents, it is necessary to develop an appropriate driver drowsiness and alertness system that can directly improve the driving safety. However, several complicated issues are involved with keeping an eye on drivers all the time to wipe out all possible hazards. Driver fatigue is a significant factor in a large number of vehicle accidents. The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its affects. The aim of this paper is to develop an algorithm for drowsiness or alertness detection system. The focus will be placed on designing a system that will accurately monitor the open or closed state of the driver's eyes in real-time . By monitoring the eyes, it is believed that the symptoms of driver fatigue can be detected early enough to avoid a car accident.

MOTIVATION

Here we are used SVM(support vector machine) to classify the components in the input video. While cropping the region of interest components in the video is not accurate. Sometimes it will show regions wrong. To sense the eyes first we have to create boundary boxes for that and a classification algorithm. The algorithm of SVM will not support. There are various methods like detecting objects which are near to vehicle and front and rear cameras for detecting vehicles approaching near to vehicle and airbag system which can save lives after an accident is accorded.

The motivation behind facial key-focuses acknowledgment is that getting the vital data about areas of eyebrows, eyes, lips also, nose in the face. With the improvement of profound learning, it is the first run-through for Sun et al. [9] to presented DCNN based on CNN to distinguish human facialkey points. This calculation just perceives 5 facialkey points, though its speed is quick. To accomplisha higher exactness for the facial key focuses acknowledgment, Zhou et al [10]. utilized FACE++ which streamlines DCNN furthermore, it can perceive 68 facial key points, however, this calculation incorporates an over the top model and the activity of this algorithm is muddled. Wu et al.[11] proposed Changed Convolutional Neural Systems (TCNN) which has a dependency on theGaussian Blend Model (GMM) to make better the various layers of CNN. In any case, the vigour of TCNN relies upon information exorbitantly. Kowalski et al. [12] presented the Profound Arrangement System (DAN) to perceive the facial key points, which has preferred execution over different calculations. Tragically, DAN needs immense models and count dependent on convoluted capacities. To meet the prerequisite about genuine-In 2016 Manu B.N [19] used a method that detects the facial landmarks using Haar feature-based cascade classifiers. At first, the algorithm must be trained by plenty of images with faces and without faces to coach the classifier to detect human faces more accurately. So along with the Haar feature- based classifiers,

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 6, June 2021

DOI 10.17148/IJARCCE.2021.10632

cascaded Adaboost classifier is exploited to acknowledge the region of the face then that image is divided into multiple numbers of rectangle areas, in any position and scale within the first image. The haar like features is healthier forreal-time face detection. These may be calculated in step with the difference of total of constituent values inside parallelogram space and through this tactic, the boost algorithm can allow all the face samples and it will ignore the non-facial samples of the images.In 2015, Amna Rahman [20] has created a method to detect the drowsiness using Eye state detection with Eye blinking strategy. During this method, first, the image is converted to greyscale and the corners are discovered using Harris corner detection rule which may detect the corner at each facet and at the down curve of eyelid. After tracing the points then it'll create a straight line between the upper two points and locates the mid-point by calculation of the road, and it connects the mid-point with the lower point. Now for every image, it'll perform the identical procedure and it calculates the space,‗d', from the mid-point to the lower point to see the eye state. At last, the selection for the attention state is created passionate about separation,'d' determined. If the distance is zero or is near zero, the attention state is assessed as ―closed‖ otherwise the attention state is identified as ―open‖. They need also invoked intervals or time to understand that the person is feeling drowsy or not. this is often done by the typical blink duration of an individual is 100-400milliseconds (i.e. 0.1-0.4 of a second). Different fromthese methods, we created a straightforward method which makes the project even more accurate and inexpensive.time execution, we utilize dlib [13] to perceive facial key points. eye blinking, head lowering, etc. In comparison to thecontact system, the non- contact system comes out to be more convenient, owing to its low cost of installation and less need for sophisticated technology. In this paper, we propose a non- contact system that uses a camera facing the driver to capture their face by monitoring the video stream continuously. On successful detection of the driver's face, we extract the facial features of the face, the region of the eye in particular, by making use of the facial landmark detection algorithm. From the eye region data, we compute the eye aspect ratio (E.A.R) [2] of the driver. Using the eye aspect ratio we can determine ifthe eyes of the driver are closed or not, as the eye aspect ratio remains a constant in the case of the eyes being open but it tends to fall and not increase againif the driver's eyes are closed for a longer period i.e., when they have dozed off behind the wheel, in such acase occurring, an alarm is sounded to wake the driver up.In such a system, the driver's face is the most important area of focus, as it conveys the most information through the driver's facial expressions, thus it is very important for the face detection part to be highly accurate. Previous such non- contact systems made use of Haar feature-based cascade classifiers for the purpose of face detection. Haarfeature-based cascade classifiers are very good at detecting lines and edges, which makes it very effective in detecting faces and it is very fast in its operation, but the drawback of using a Haar feature- based system is that the results can tend to be notvery accurate. In the case of a driver wearing glasses of any kind, this system would fall short in the task offace detection. Thus, to overcome this problem of inaccuracy and detect the driver's face, we use a Histogram of Oriented Gradient (HOG) featuredescriptor, in which the distribution (histograms) of directions of gradients (oriented gradients) are usedas features. This descriptor is more accurate than the previously discussed system as it is generated on a dense grid of uniformly spaced cells and makes useof local contrast normalization that is overlapping in nature.This HOG descriptor is combined with a Linear Support Vector Machine (SVM) into which the feature vector from the HOG algorithm is fed for the purpose of image classification, as a Linear SVM can be used to train highly accurate object classifiers [3]. After successful face detection, we will require proper facial landmark detection to be done, and for this purpose, we make use of the facial landmark detector available in dlib library, which is a general- purpose cross-platform library. The facial landmark detector which is used in dlib library is an implementation of One Millisecond Face Alignment with an Ensemble of Regression Trees [4]. This method works by training a set of marked facial landmarks on an image. These images are manually marked, by using the specific (x, y)-coordinates of the areas around each facial structure. By making use of this trained data, a collection of regression treesare trained to compute the facial landmark positions using the pixel intensities. Through this, we arrive ata facial landmark detector that can successfully detectfacial landmarks in real-time with high-quality predictions. By using the coordinates of the position of the eyes, we can compute the Euclidean distance which is used for the eye aspect ratio. Using this eye aspect ratio, we determine if the driver has shown signs of sleepiness and take necessary action in the form of an alarm.The contribution of this paper is the HOG facial descriptor algorithm working with the Linear SVM classifier for highly accurate image classification and in turn, better face detection, which results in a more reliable system for providing drowsiness alerts to the drivers

PROPOSED SYSTEM

To deal with this problem and provide an effective system a drowsiness detection system can be developed which can be placed inside any vehicle which will take live video of the driver as input and compare with training data and if the driver is showing any symptoms of drowsiness system will automatically detect and raise an alarm which will alert the driver and other passengers. There are several different algorithms and methods for eye tracking, and monitoring. Most of them in some way relate to features of the eye (typically reflections from the eye) within a video image of the driver.

A. Initial Camera Setup:

The first step in the system would be to set up a camera facing the driver so that we can provide successful capturing

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 6, June 2021

DOI 10.17148/IJARCCE.2021.10632

of the driver‘s face for the purpose of further processing. The camera must be set up in such a way that it is not intrusive, i.e., does not get in the way of the driver while on the road and must be placed in a proper manner so that the face captured is clear and so provides accurate results

B. Face detection:

The next step involved is detecting the face of the driver that is displayed on the video stream. To extract the facial landmarks of drivers, Dlib library was imported and deployed in our application.The library uses a pre-trained face detector, which is based on a modification to the histogram of oriented gradients and uses linear SVM (support vector machine) method for object detection. Actual facial landmark predictor was then initialized and facial landmarks captured by the application were used to calculate distance between points. EAR is defined as the ratio of height and width of the eye and was computed using equation 1. The numerator denotes the height of the eye and the denominator denotes the width of the eye and the details of the all the landmarks of eye are depicted by figure 1.

Referring equation 1, the numerator calculates the distance between the upper eyelid and the lower eyelid. The denominator represents the horizontal distance of the eye. When the eyes are open, the numerator value increases, thus increasing the EAR value, and when the eyes are closed the numerator value decreases, thus decreasing the EAR value. In this context, EAR values are used to detect driver’s drowsiness. EAR value of left and right eyes is calculated and then average is taken. In our drowsiness detector case, the Eye Aspect Ratio (K. C. Patel, S. A. Khan, and V. N. Patil,2018) is monitored to check if the value falls below threshold value and also it does not increases again above the threshold value in the next frame. The above condition implies that the person has closed his/her eyes and is in a drowsy state. On the contrary, if the EAR value increases again, it implies that the person has just blinked the eye and there is no case of drowsiness. Figure 2 depicts the block diagram of our proposed approach to detect driver’s drowsiness. Figure 3 represents a snapshot of facial landmark points using Dlib library, which are used to compute EAR.

C. Face landmark Detection and Extraction:

The next step involved after successful face detectionis recognizing the facial landmarks and extraction of the desired facial landmarks. Finding facial landmarks can be done by several methods, but most of the methods work on labeling and localizing the regions such as the right eyebrow, left eyebrow, right eye, left eye, nose, mouth and, jaw. We use the facial landmark detector algorithm which is an implementation of the One Millisecond Face Alignment with an Ensemble of Regression Trees[4]. This detector algorithm is a part of the dlib library. This method works by manually labeling, specific (x,y) coordinates for the regions surrounding each facial structure and using this set of trained facial landmarks on an image. This detector availablein dlib library estimates the location of the 68 (x,y) coordinates that are specific to each separate facial structure. The 68 facial landmark coordinates can be visualized in Fig.2.

Fig.1. Visualizing the 68 facial landmark

coordinates We can localize and extract the eye regions bymaking use of the specific facial indices for the leftand right eye regions. The right eye can be accessedby using the coordinates [36,42] and, the left eye canbe accessed by using the coordinates [42,48]. Theseindices are a part of the 68 points iBUG 300-w [21]-[23] dataset on which the facial landmark detector available in dlib library is trained. Irrespective ofwhich dataset is used, if the shape predictor is trainedproperly on the input training data, the same dlib framework can be used.

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 6, June 2021

DOI 10.17148/IJARCCE.2021.10632

D. Eye Aspect Ratio (E.A.R) Computation:

To detect if the driver‘s eye is closed or not, and to also successfully differentiate between standard eye blinks and eyes being closed during a state of drowsiness, we make use of an algorithm that uses a facial landmark detector. We compute a single, scalarquantity called eye aspect ratio (E.A.R) [2] that reflects whether the eye is closed or not. For each video frame, the landmarks of the eye regions are found, and the Euclidean distance using the height and width of the eye is calculated, which is the eye aspect ratio (E.A.R).

$$\text{EAR} = \frac{\|1-5\| + \|2-4\|}{\|0\text{-}3\|}$$

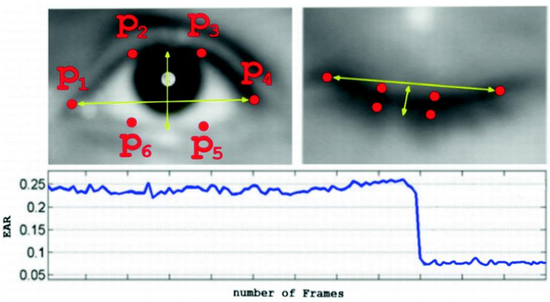

Fig.2. Eye landmarks

where P1, P2, P3, P4, P5, and P6 are the 2D landmarklocations, depicted.

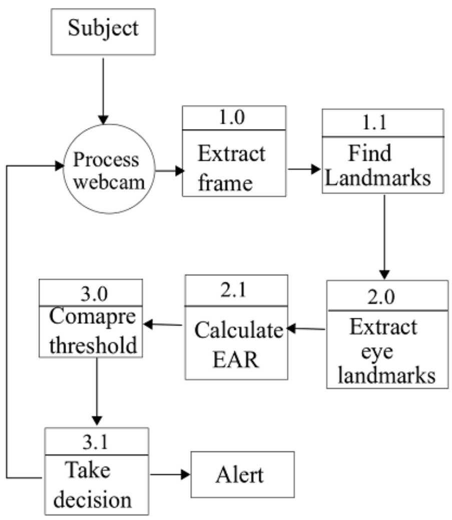

Fig.3.Block diagram of proposed system

E. Drowsiness Evaluation and counter measures:

After we successfully compute E.A.R, we can use that value to evaluate the driver‘s state of drowsiness. The E.A.R value remains constant when the eye of the driver is open, but it starts to reduce to a value close to zero when the eye starts to close. E.A.R is invariant with respect to head and body posture. So, using these findings we can classify the eye state as closed when the E.A.R is 0.3 or less than 0.3, otherwise the state is identified as open.
The final part is making the decision to sound the alarm or not. The average duration of a person‘s eye blink is 100-400 milliseconds, hence if the driver is in a state of drowsiness, their eye closure time is beyond this interval. In our system, the threshold is set 0.3 seconds, and if this is crossed the alarm is sounded and an alert regarding this will pop.

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 6, June 2021

DOI 10.17148/IJARCCE.2021.10632

CONCLUSION:

We successfully developed a sleepiness detection system to look out for the fatigue within the drivers in real-time that helps avoid accidents due to sleepiness. The system has a face and eye blinking detection formula based upon the Histogram of Oriented Gradients (HOG) image descriptor and a Linear Support Vector Machine (SVM) facial detectors. These are precise enough to reliably estimate the positive photos of the face and level of eye openness. Moreover, the results show that it's having a higher accuracy even within the low light conditions.

REFERENCES:

[1] CISR- Central Road Research Institute, ―https://www.crridom.gov.in/‖

[2] Tereza Soukupova and Jan Cech, Center for Machine Perception, Department of Cybernetics Faculty of Electrical Engineering, Czech Technical University in Prague, ―Real-Time Eye Blink Detection using Facial Landmarks‖, 21st Computer Vision Winter Workshop Luka Cehovin, Rok Mandeljc, Vitomir Struc (eds.) Rimske Toplice, Slovenia, February 3–5, 2016.

[3] Navneet Dalal and Bill Triggs, INRIA RhoneAlps, ˆ 655 avenue de l'Europe, Montbonnot 38334, France, ―Histograms of Oriented Gradients for Human Detection‖.

[4] Vahid Kazemi, Josephine Sullivan, ―One millisecond face alignment with an ensemble of regression trees‖, IEEE Conference on Computer Vision and Pattern Recognition 2014.

[5] Bruce D. Lucas and Takeo Kanade, ―An iterative image registration technique with an application to stereo vision,‖ in Proceedings of the 7th International Joint Conference on Artificial Intelligence- Volume 2, San Francisco, CA, USA, 1981, IJCAI'81, pp. 674–679, Morgan Kaufmann Publishers Inc.

[6] D. S. Bolme, J. R. Beveridge, B. A. Draper, and Y. M. Lui, ―Visual object tracking using adaptive correlation filters,‖ in Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition, June 2010, pp. 2544–2550.

[7] Yang Li and Jianke Zhu, ―A scale adaptive kernel correlation filter tracker with feature integration,‖ in Computer Vision - ECCV 2014 Workshops, Lourdes Agapito, Michael M. Bronstein, and Carsten Rother, Eds., Cham, 2015, pp. 254–265, Springer International Publishing.

[8] M. Danelljan, G. HÃd'ger, F. S. Khan, and M. Felsberg, ―Discriminative scale space tracking,‖ IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 8, pp. 1561– 1575, Aug. 2017.

[9] Y. Sun, X. Wang, and X. Tang, ―Deep convolutional network cascade for facial point detection,‖ in Proc. IEEE Conf. Computer Vision and Pattern Recognition, June 2013, pp. 3476–3483.

[10] E. Zhou, H. Fan, Z. Cao, Y. Jiang, and Q. Yin, ―Extensive facial landmark localization with coarse-to-fine convolutional network cascade,‖ in Proc. IEEE Int. Conf. Computer Vision Workshops, Dec. 2013, pp. 386–391.

[11] Y. Wu, T. Hassner, K. Kim, G. Medioni, and P. Natarajan, ―Facial landmark detection with tweaked convolutional neural networks,‖ IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 12, pp. 3067–3074, Dec. 2018.

[12] M. Kowalski, J. Naruniec, and T. Trzcinski, ―Deep alignment network: A convolutional neural network for robust face alignment,‖ in Proc. IEEE Conf. Computer Vision and Pattern Recognition Workshops (CVPRW), July 2017, pp. 2034–2043.

[13] Davis E. King, ―Dlib-ml: A machine learning toolkit,‖ J. Mach. Learn. Res., vol. 10, pp. 1755– 1758, Dec. 2009.

[14] B. Warwick, N. Symons, X. Chen, and K. Xiong, ―Detecting driver drowsiness using wireless wearables,‖ in Proc. IEEE 12th Int. Conf. Mobile Ad Hoc and Sensor Systems, Oct. 2015, pp. 585–588.