EFFICIENT LOCALIZATION OF REGION OF INTEREST FOR DROWSINESS DETECTION

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Abstract: *The vehicle population is growing exponentially in the country. The increase in the number of road accidents is the main problem associated with increased traffic. The drowsiness, alcoholism and negligence of drivers are the main actors in the accident scenario. Road accidents are a big problem today and their percentage is increasing every year. Drowsiness is one of the factors of collision. In India, no monitor is used to measure drowsiness of the driver. Therefore, extraction or region of interest (ROI) is important to detect driver drowsiness. The proposed algorithm estimates landmark positions and extracts the eye region using eye aspect ratio (EAR). An SVM classifier algorithm is used to identify eye regions.*

Keywords*- ROI, SVM , EAR*

1. INTRODUCTION

Detection of driver drowsiness is a vehicle safety technology that controls accidents when the driver becomes sleepy. Driver fatigue is a major factor in many road accidents. Road accidents are a big problem today and their percentage is increasing every year. The development of technologies to detect or prevent driver fatigue is a major challenge for accident prevention systems. Because of the risk of drowsiness on the road, methods must be developed to counteract their effects. Driver inattention may be due to a lack of attention while driving due to sleepiness and driver distraction. Driver distraction occurs when an object or event distracts the person from the driving task. Unlike driver distraction, driver drowsiness causes no triggering events, but a gradual withdrawal of attention from the road and traffic demands. However, drowsiness and driver distraction can have the same effect, reduced driving performance, longer exposure time and increased risk of accident participation. In this proposal, a real-time algorithm for detecting blinking in a video sequence from a standard camera is proposed. More recent landmark detectors formed on wild-type data sets have greater robustness with respect to head alignment with respect to a camera, different illumination, and facial expressions. Here, the landmarks are recognized so that they can estimate the height of the eye opening. The proposed algorithm estimates landmark positions and extracts the quantity-eye aspect ratio (EAR). An SVM (Support Vector Machines) classifier identifies blink with EAR values. The Viola Jones detector is a typical method of detection of the face and eyes. In this movement, the eye area estimated by sparse tracking. Finally, it is decided whether the eyes are closed or not. The main disadvantage of this approach, is that the implicitly configure is too high requirements setup. For example, relative position of the camera for the face or alignment of the head, resolution of the image, etc. An image of the human face, including the corners of the eyes and eyelids, is available. Figure 1 shows the landmarks of the eye. There are 6 landmarks (p1, .., p6). These marker detectors are trained on the wild datasets and are therefore resistant to different lights and facial expressions. An average error of localization is below five percent. The new methods work very well in real time.

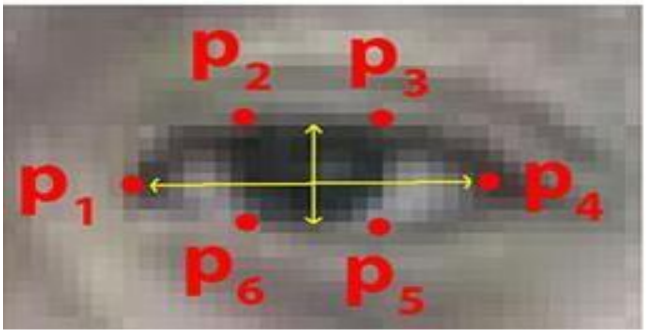


Figure 1: *Open eyes with landmarks pi*

The eye aspect ratio (EAR) is calculated for the _opened eyes. When eye is opened aspect ratio remains constant. But, when eye is closed, eye aspect ratio closes to zero which indicates that eye is blinked.

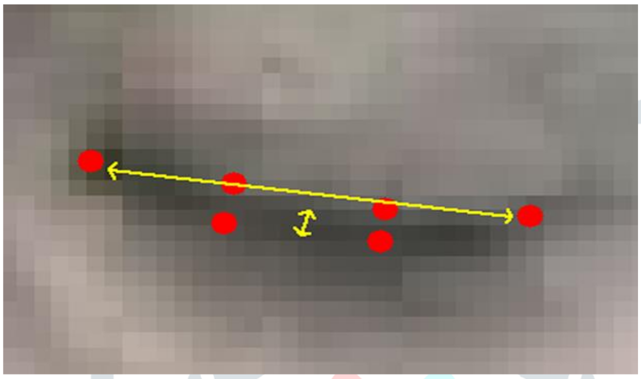


Figure 2: *Closed eyes with landmarks pi*

Eye aspect ratio is plotted for several frames of videos. In figure 3 we can see that when eyes is open EAR remains unchanged but when eyes are closed it reaches to zero.

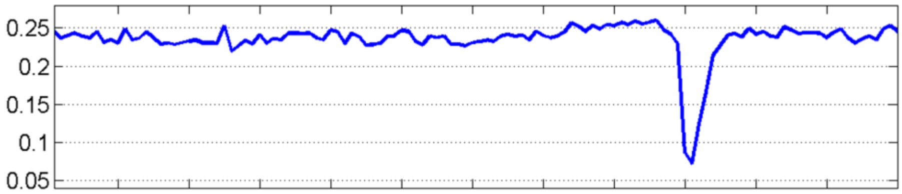


Figure 3 : *Eye aspect ratio is plotted for several frames of videos.*

To pinpoint drowsiness, we suggest an efficient algorithm for detecting eye blinks from landmarks. From the landmarks, a single scalar quantity is derived that reflects a plane of the eye opening. As a result, we get a sequence of eye openings per image that estimates that the eye is blinking. Blink is found by an SVM that stands for Support Vector Machines and has been trained on examples of blinking and non-blinking patterns. Therefore, the drowsiness of the driver is accurately identified in consideration of eye features and eye conditions. Once the drowsiness of the driver is detected, the driver is alerted by the alarm in the vehicle. He is also notified of the message being sent to his mobile phone via the GSM modem.

2. PROPOSED METHOD

The blink is a quick closing and reopening of a human eye. Each individual has a different blink pattern. The model differs in the speed of closing and opening. The blink takes about 100 to 400ms. From the landmarks identified in the image, we obtain the aspect ratio of the eye (EAR), which is used to estimate the conditions of opening of the eye. Since the per-image EAR does not necessarily detect that the eye is blinking properly, temporal window of a frame is trained by the classifier.

2.1 Feature Description

The eye landmarks are detected for every video frame .The aspect ratio of the eye (EAR) between the height and the width of the eye is calculated.

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

Where p1, ..., p6 are the 2D landmarks (see Figures 1 and 2). EAR is generally constant when an eye is open and approaching zero when the eye is closed. The aspect ratio of the open eye is slightly different in individuals and is completely invariable for uniform scaling of the image and rotation of the face in the plane. Since both eyes blink synchronously, the average EAR of both eyes is calculated.

2.2 Classification

This does not usually mean that a low EAR value means that a person is blinking. A decrease in EAR may occur when a subject voluntarily closes their eyes for a long time, makes a facial expression, or the EAR detects a brief random fluctuation of landmarks. As a result, the proposed classifier uses a larger temporal window for a frame as a input. We use here a linear SVM classifier called EAR SVM, which results in manually annotated sequences. Positive examples are collected when truth on the ground is blinking, and sampled parts of the video that are not blinking are considered as negative examples. During the test, a classifier is executed in an analysis window. A 13-dimensional feature is computed and classified by EAR SVM for each frame, except for the beginning and end of a video clip.

2.3 Experiment Carried

One experiment was carried out that measures the landmark detectors accuracy.

Accuracy of landmark detectors: The following tests are intended to demonstrate that the new landmark detectors are particularly robust and accurate in the detection of eyes, i.e. The corner of the eye and the contour of the eyelids. That's why we have prepared a dataset, a subset of the 300-VW, which contains examples of images with open and closed eyes. Specifically, with truth-based truth annotation, we sorted the frames of each subject according to the format of the eye and selected 10 frames with the highest ratio (eyes wide open), 10 frames with the ratio the lowest (usually closed eyes) and 10 images were randomly selected. In this way, we collected 1500 images. In addition, all the images were then down sampled to evaluate the accuracy of the detectors tested on small facial images. The accuracy of recognition of a landmark on a facial image is measured by the relative mean error of landmark location, defined as follows:

$$\epsilon = \frac{100}{\kappa N} \sum_{i=1}^{N} \|x_i - \hat{x}_i\|_2.$$

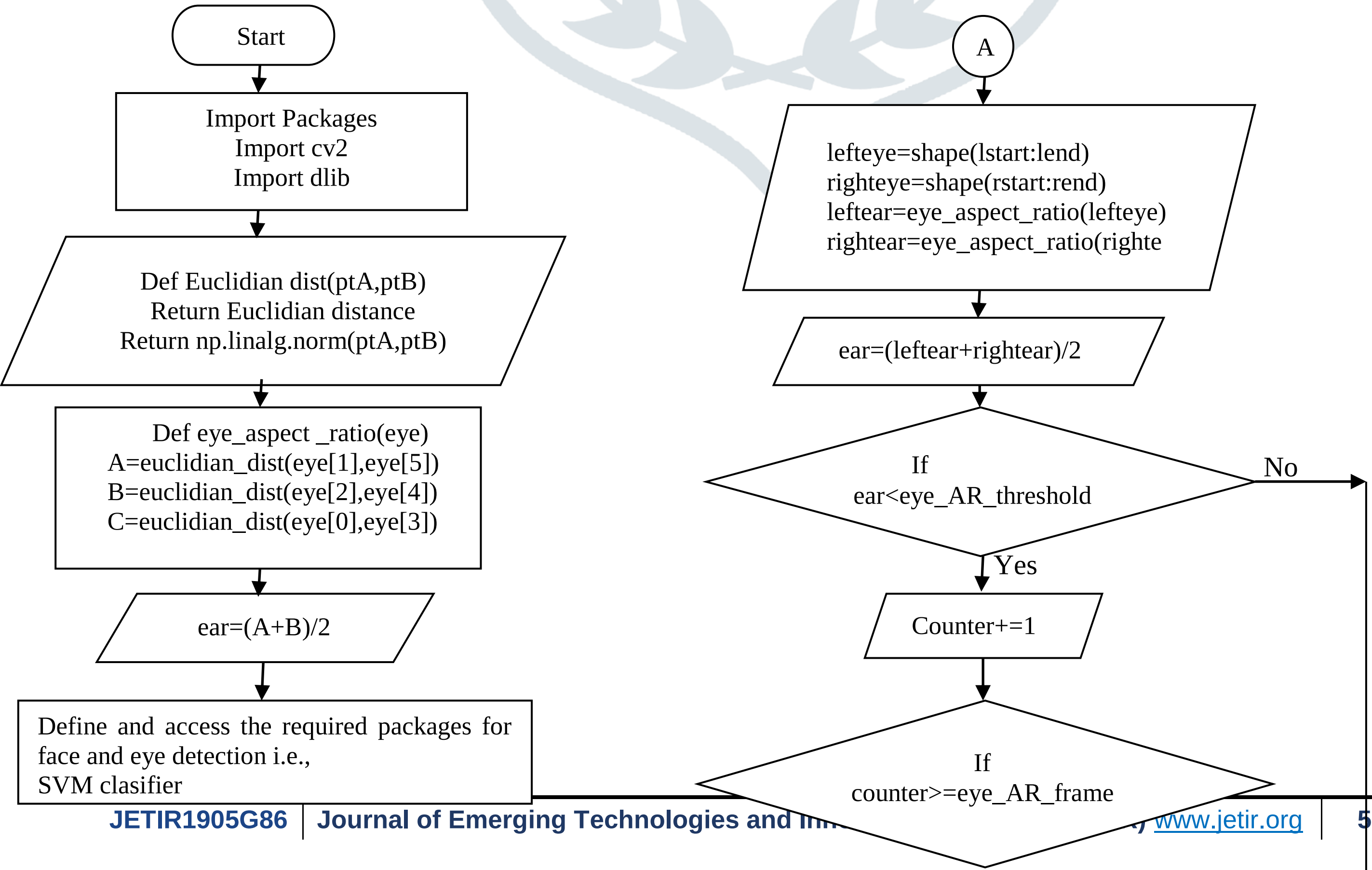
Where xi is the location of the ground truth of the landmark i in the image, xi is an estimated location of the landmark by a detector, N is a number of landmarks and the normalization factor k is the inter ocular distance (IOD), i.e the Euclidean distance between the eyes image.

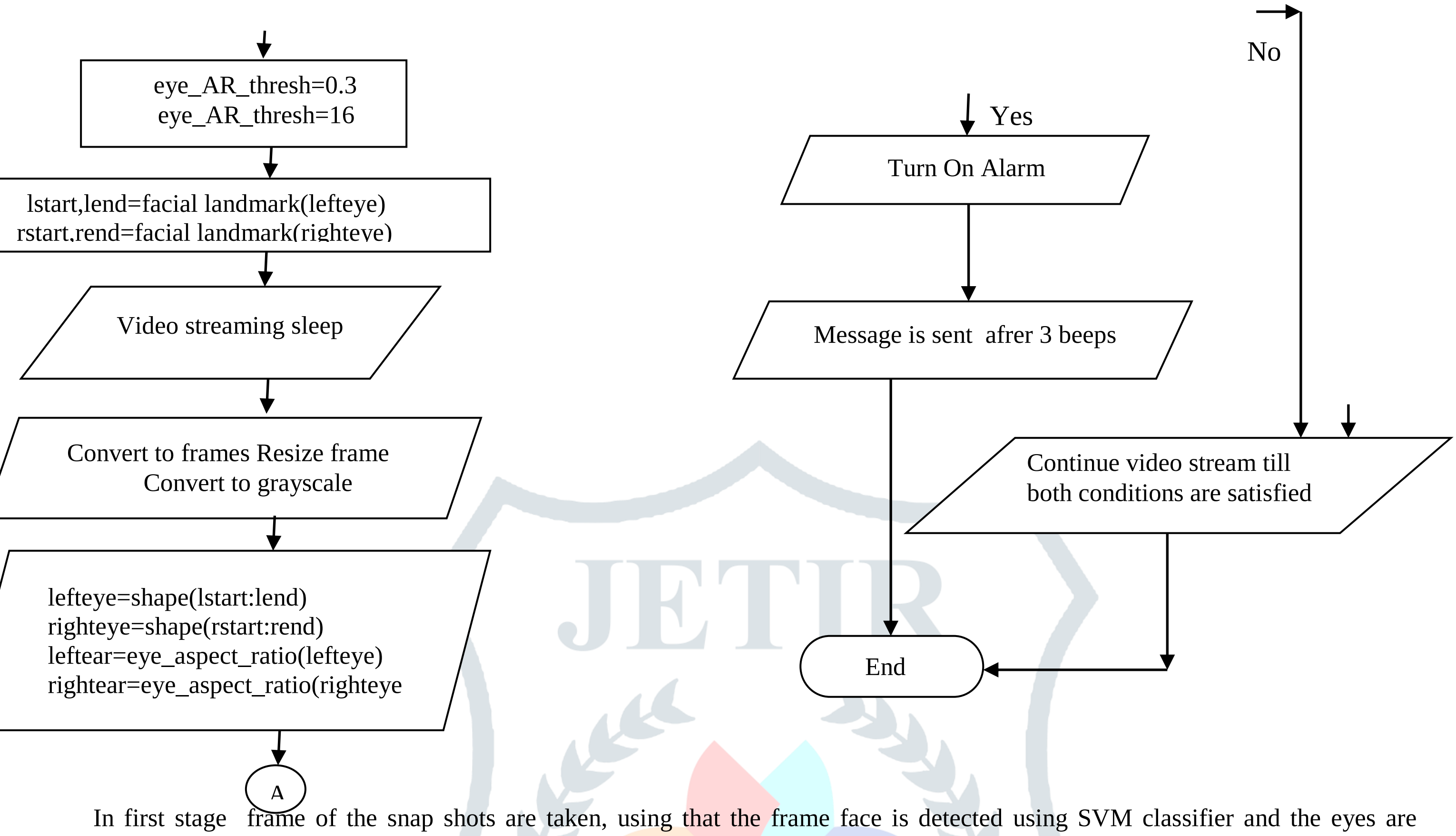
Figure 4 : *Detection of eye blinking and Calculating EAR for blinked eyes*

In above figure detection of eye blinking and calculating EAR for blinked eyes are presented. The eye landmarks are located so that it can extract only eye regions. We are interested in finding which eye is blinked, whether it is left or right eye which is displayed in figure 4. Along with the detection of eye blinking we are also calculating eye aspect ratio for the eyes. In driver drowsiness detection system, we have set a threshold value for eye aspect ratio. Whenever a person closes his eyes for more than three seconds and when EAR reaches to threshold value, we can say that drowsiness is detected. In our system, driver will be alerted about the drowsiness by making use of buzzer and the message features. When driver closes his eyes for more than three seconds, a alarm will be buzzed and a message "drowsiness detected" will be displayed on the screen and message will be sent to the owner .

3. FLOWCHART

This section includes how the driver drowsiness detection is implemented using SVM classifier algorithm.





In first stage frame of the snap shots are taken, using that the frame face is detected using SVM classifier and the eyes are cropped from the frame using certain calculations and then the cropped eyes are converted into binarization form. Same process continues for the next inputs. In second stage the eye percentage of each binarized frames are calculated and is compared with each other and final results are computed. In the stage of result if driver closes his/her eyes for more than three seconds it is considered as sleepy state and then the alarm is issued and "drowsiness detected" is displayed on the screen. After three beeps of alarm message is sent to the registered mobile number using GSM modem. Otherwise it returns no and then goes back to the initial state of camera.

4. CONCLUSION

We have proposed an SVM classification algorithm to detect eye blinking in a driver fatigue detection system that uses a temporal window of the eye height / width ratio. On the other hand, the threshold is used as a single image classifier to detect the eye condition if the sequence is no longer available. We see a limitation in the fact that a fixed blink duration has been assumed for all subjects, although blink lasts for all differently. The results could be improved by an adaptive approach. Another limit is the estimate of the opening of the eyes. While EAR is estimated from a 2D image, it is quite insensitive to the orientation of the head. We can improve this problem by defining the EAR file in 3D. There are landmark detectors that estimate the 3D position (position and orientation) of a 3D landmark model. Using this improved algorithm, we can implement a driver fatigue detection system that delivers the expected results. It is very important to use the best algorithm to implement a system.

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