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Computer vision and its role in driving safety

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ABSTRACT

Every year there are more than 1.2 million road accidents happening across the globe, which accounts for more than 2.2% of deaths on a global scale. There has been an alarming increase of road accident in today's time and a major reason behind this can be attributed to how the driver is behaving during his driving. Some of them may be unavoidable, yet a major portion of the hazards may be averted if there are means to keep a check on driver state ranging from their physical condition to monitoring their reckless driving patterns. This is where the advent of technology and role of having a robust monitoring ecosystem comes into the picture. Computer Vision, more or less is a sought after technology which automotive companies today are chasing, be it telematics based connected cars or autonomous self-driving vehicles. It can help solve this purpose by monitoring the driver drowsiness through advanced image processing solutions and providing the user with an integrated report showcasing how concentrated their driving was and what needs to be improved. This image processing technique may also be integrated in Telematics products to provide results on what the eco-driving score of the user is and may be alerted via notifications on smartphone as to what daily trends of their driving are. This solution proves to be an effective approach to counter and restrict the increasing number of road accidents happening across the globe and meet end goal of achieving the maximum safety out of the road-network ecosystem.

Keywords: *Computer Vision, Connected-Cars, Image processing, driver drowsiness, IoT, Analytics*

1. INTRODUCTION

Driver drowsiness resulting in reduced vehicle control is one of the major causes of road accidents. Driving performance deteriorates with increased drowsiness with resulting crashes constituting 20%-23% of all vehicle accidents. The National Highway Traffic Safety Administration (NHTSA) conservatively estimates that 100 000 reported crashes are caused by drowsy drivers each year in the U.S. alone. These crashes result in more than 1500 fatalities, 71 000 injuries, and an estimated $12.5 billion in diminished productivity and property loss. Many efforts have been made recently to develop on-board detection of driver drowsiness. A number of approaches have been investigated and applied to characterize driver drowsiness using advanced computer vision, image processing and eye movement detection algorithms.

A driver state of drowsiness can also be characterized by the resulting vehicle behaviour such as the lateral position, steering wheel movements, and time-to-line crossing. Although these techniques are not intrusive, they are subject to several limitations related to the vehicle type, driver experience, and geometric characteristics and condition of the road. Among these various possibilities, the monitoring of a driver's eye state by a camera is considered to be the most promising application due to its accuracy, cost effectiveness and non-intrusiveness. The driver's symptoms can be monitored to determine the driver's deviation from normal state, early enough to take preventive actions to avoid an accident.

2. METHODOLOGY

Our objective is to determine driver's "state of concentration" for two cases. The term "state of concentration" simply means the deviation of driver's behavior from the usual one. The two cases are as follows:

CASE I

When the driver is driving, his/her eyes should not be closed for more than threshold time (**ThrTime1)** for more than a threshold number of time (**ThrCount).** Upon occurrence of the above event we simply detect an event and reset the counter to look for a new event.

CASE II

We are monitoring the facial orientation of the driver as well as the 3-axis acceleration values of the vehicle. When vehicle is going along a particular axis intended behavior is that driver's facial orientation will be ± tolerance angle (**ThrAngle)** from the direction vector of the axis for more than a threshold time (**ThrTime2**). Any deviation from this will be considered as an event. This case can be further improved by accommodating steering rotation direction which will be particularly helpful to accurately detect left & right turns. It is described in the below fig 1.

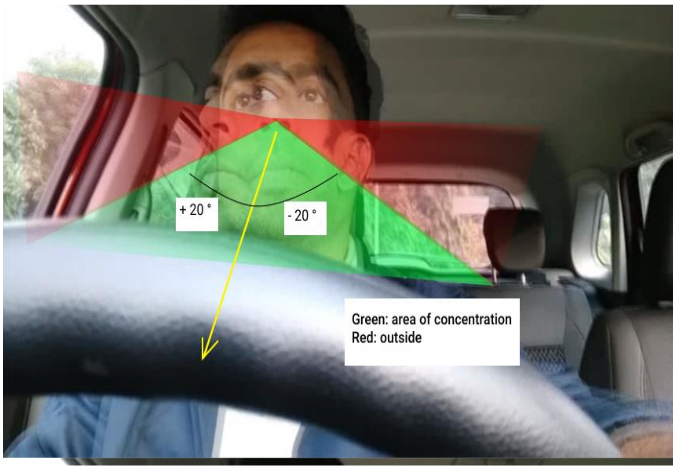

Fig. 1: ThrAngle

For detecting facial landmarks we used Python dlib library. dlib has already defined co-ordinates for facial landmarks which is shown in the below fig 2:

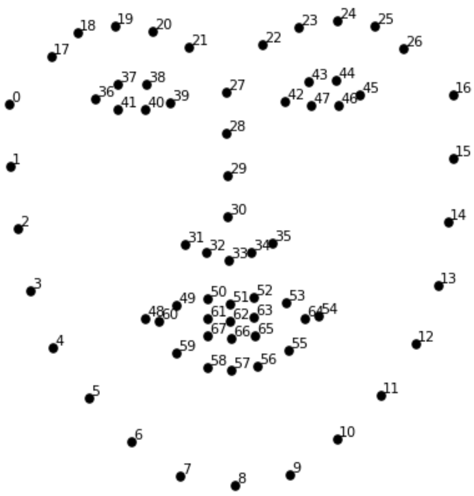

Fig. 2: Facial landmarks

We have two objectives to accomplish:

Objective I: Detection of eye closure frame by frame of the video captured through camera.
Objective II: Detection of facial orientation.

Objective I can be easily achieved as dlib's shape predictor accurately predicts the defined co-ordinates. Our area of concentration is points from 36 to 41 (left eye) and 42 to 45 (right eye). Eye can measure the Euclidean distance between (37, 42), (38, 40) for left eye and (43, 47), (44, 46) for right eye to predict eye closure.

Based on a research work by Tereza Soukupova and Jan ´ Cech published in a paper named "Real-Time Eye Blink Detection using Facial Landmarks" we can accurately detect eye closure. Consider the below figure 3

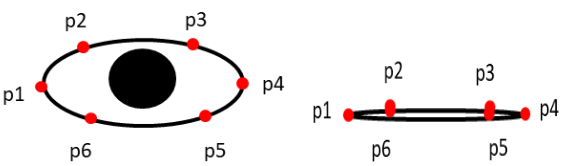

Fig. 3: Eye closure

We can define eye aspect ratio (EAR) based on the points p_i As:

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

EAR will small when eye is closed and high when eye is opened.

For our case we will be getting two EAR namely EAR_{left} for left eye and EAR_{right} for right eye.

So effective EAR is

$$EAR_{effective} = \min(EAR_{left}, EAR_{right})$$

We kept the threshold to detect eye closure at < 0.2. So for successful eye detection:

$$EAR_{effective} < 0.2$$

For **object II** we used the facial landmark points and mapped them in 3D co-ordinates. Then we measured the translation vector and rotation matrix to determine the pose of the face. We considered the below 6 landmark points

a) Tip of the nose
b) Chin
c) Left corner of the left eye
d) Right corner of the right eye
e) Left corner of the mouth
f) Right corner of the mouth

These above 6 co-ordinates are called **World Coordinates** or Model Co-ordinates in terms of Python OpenCV documentation.

Let, the rotation matrix is R

$$R = \begin{bmatrix} R_{00} & R_{01} & R_{02} \\ R_{10} & R_{11} & R_{12} \\ R_{20} & R_{21} & R_{22} \end{bmatrix}$$

And, translation vector t

$$t = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$$

If (U, V, W) are the World co-ordinates and (X, Y, Z) are the camera co-ordinates then

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} R_{00} & R_{01} & R_{02} & t_x \\ R_{10} & R_{11} & R_{12} & t_y \\ R_{20} & R_{21} & R_{22} & t_z \end{bmatrix} \begin{bmatrix} U \\ V \\ W \\ 1 \end{bmatrix}$$

We have used OpenCV's *cv2.cv2.SOLVEPNP_ITERATIVE* to solve the above linear equation.

After detecting an event our object is to notify the driver though in-car notification system as well as his/her relatives via social messaging platform or any dedicated mobile application. The IoT architecture is described in figure 4. (*CAN stands for controller area network)

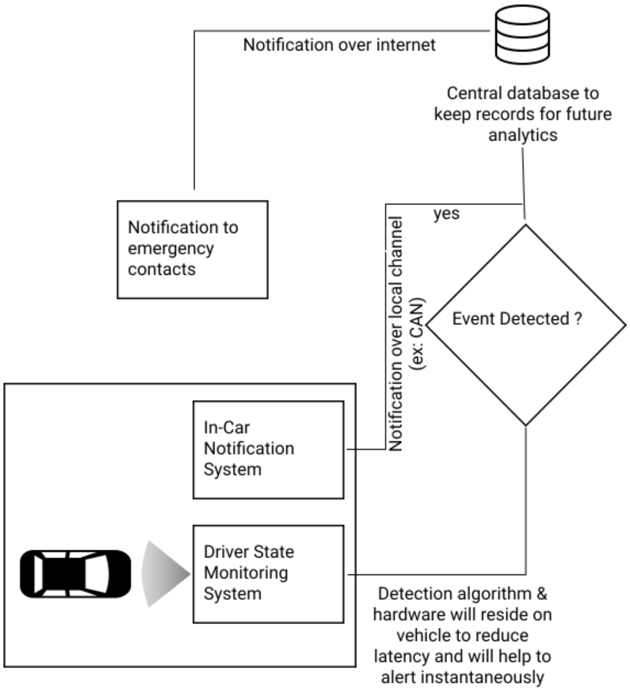

Fig.

Fig. 4: CAN stand for controller area network

3. TEST SCENARIOS

For our test cases we kept **ThrTime1** as 2 seconds and **ThrCount** as 4 i.e. driver has to close his eyes for more than 4 times, each time eye should be closed for more than 2 seconds while considering Case I.

```
ThrTime1 = 2 //in seconds
eyeClosedCount = 0
while (True):
   if (eyeCloseDetected):
      time = calculateEyeClosureTime()
      if (time > 2):
     eyeClosedCount += 1
      if (eyeClosedCount > 4):
         evenDetected()
         eyeClosedCount = 0
```

Similarly, for caseII we kept **ThrAngle** as 20 degrees and ThrTime 2 as 20 seconds. Violation this rues will create creation of an event.

4. CONCLUSION

Our code is written in Python. We used libraries like cv2, dlib, scipy and numpy for our operation. Below are the samples output upon running the code. We performed the operation inside vehicle for demonstrating real scenario.

Fig. 5: Normal condition:

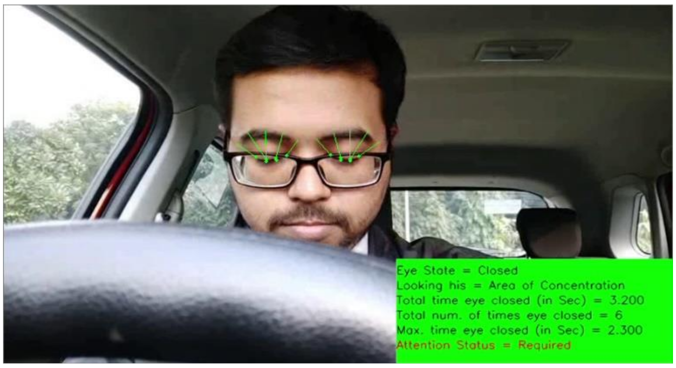

Fig. 6: Eye close detected

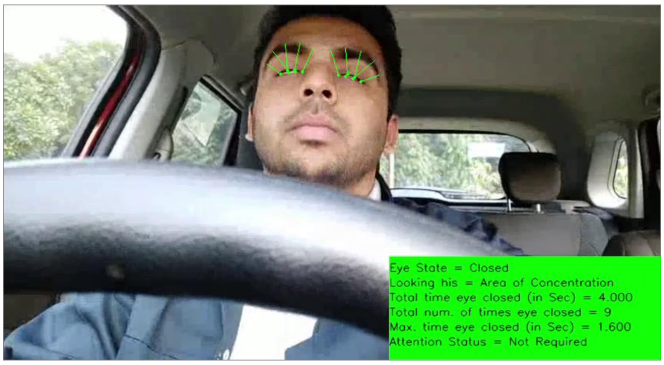

Fig. 7: Eye close detected but thresholds are not met

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Fig. 8: Looking extreme right of driver

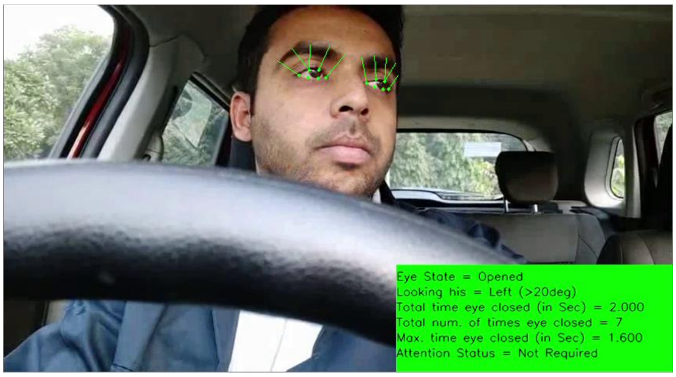

Fig. 9: Looking extreme left of drive

Fig. 10: Looking right for long time although vehicle is going forward

5. FUTURE ACTION PLAN

As part of future implementation of this algorithm it is imperative to note how the computer vision can be used effectively to monitor the driver driving pattern and alert them in case of any negligence observed. This could in return help reduce the number of road accidents and aware the drivers about a potential warning system installed within the vehicle. This method if successful maybe very effective in applying the driver behaviour analytics and using the data to generate value out of it. The findings could give an indication of the actual drive patterns and help generate an important factor in determining the driving behaviour and the driver ranking.

This could help in assigning the ratings of the drivers being served in fleet management solutions like Uber, Ola etc. What if we are able to get a score based on our driving pattern which helps restrict rash driving and keep safety as topmost priority element. Computer Vision and advanced neural network can help solve this purpose by monitoring the driver drowsiness through advanced image processing solutions and providing the user with an integrated report showcasing how concentrated their driving was and what needs to be improved. Also based on the facial orientation we can read the sign boards out loud to further assist the driver if he /she is looking at a sign board for long time.

This image processing technique may also be integrated in Telematics products to provide results on what the eco-driving score of the user is and may be alerted via notifications on smartphone as to what daily trends of their driving are. This solution proves to be an effective approach to counter and restrict the increasing number of road accidents happening across the globe and meet end goal of achieving the maximum safety out of the road-network ecosystem.

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