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Driver Hypovigilance Detection for Safe Driving using Infrared Camera

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Abstract - **Driver safety can be made possible by continually monitoring the hypovigilance of the driver. Researchers have worked on analysing the driver drowsiness or inattention detection by using the camera mounted on the vehicle. This paper works on Infrared camera based monitoring of the hypovigilance (normal, fatigue, drowsy, visual and cognitive inattention) which is nothing but monitoring the state of the driver during different timings of the day. The simulator based environment was used to monitor and record the behaviour of the driver continuously for a period of two hours. The raw video is filtered and the features were extracted and classified using Support Vector Machine (SVM), k-Nearest Neighbour (KNN) and Ensemble classifier algorithm. The average accuracy of fusion of hypovigilance state for Behavioural measure is 64.1%.**

Keywords: Image, Hypovigilance, Drowsiness, Fatigue, Visual and Cognitive Inattention

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I. INTRODUCTION:

Safe driving is an important requirement for avoiding road accidents. But accidents occur due to many causes which are unpredictable. Human are prone to compromise on safety by using mobile phones while driving, listening to music, drowsiness, drunken driving, over speeding, etc. which are the major reasons for road accidents. All these lead to heavy health and economic loss including loss of human life, injuries, fatalities and damaged properties. In India, road accidents have increased by 0.46% compared to previous year as provided in the report by the Ministry of Road Transport and Highways [1]. As the report issued by the National Road Safety Authority, there is a 10% increase in the death rate at Israel in 2019 when compared to the previous year (349 people killed in 2019 vs 314 in 2018) [2]. Many advanced technologies are developed by government and automobile industries to reduce the impact of road accidents. But still the annual statistics shows, no degradation in the death rate.

Hypovigilance means ‘diminished vigilance’ or ‘diminished alertness’ which is defined as anything that causes a decrease in paying a close and continuous attention [3]. Researchers have worked on combination of measures to detect driver hypovigilance involving both individual driver behaviour and behaviour of the combined set of drivers. The various measures used are

- Subjective measure;
- Behavioural measure;
- Physiological measure; and,
- Vehicle-based measure.

Behavioural measure with good lighting condition is much suitable for Driver Hypovigilance Detection. Many researchers have used vision-based method for determining the driver behaviour. Driver fatigue detection consists of head-shoulder detection, face detection, eye detection, eye openness estimation, drowsiness measure, percentage of eyelid closure (PERCLOS) estimation and fatigue level classification [4]. A video-based drowsiness recognition method is presented in [5]; they extract the following features related to the eyes of the driver: PERCLOS, maximum closure duration, blink frequency, average opening level of the eyes, opening velocity of the eyes and, closing velocity of the eyes, to predict the driver fatigue with 86% accuracy. [6] Uses circularity, black ratio along with wavelet coefficients and texture features to detect driver drowsiness with the accuracy of 91.3%. In low light conditions, the techniques presented in [7] detects face, eyes, mouth of the driver and subsequently the actions of eye closure and yawning with the accuracy of 98% and 92.5% respectively. Using facial dynamic fusion information and a Deep Belief Network (DBN), facial drowsiness expressions are classified with an average accuracy of 96.7% by the techniques presented in [8]. A non-intrusive approach presented in [9] uses Histogram Oriented Gradient (HOG) for face detection and facial points recognition, Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to check sleepiness and yawning of driver. As stated in [10] eye detection using Viola-Jones algorithm and iris detection using circular Hough Transform technique has achieved an accuracy of 99% during daytime, 96% during night-time and 91% for noisy frames.

A low-power system iLid, developed to measure blink duration and PERCLOS to detect fatigue and drowsiness with less than a few percent error is presented in [11]. Eye and Mouth state analysis presented in [12] uses EyeMap algorithm and internal mouth contour to extract sclera-fitting eye contour and analyse the opening state of mouth for yawning detection. An on board i.mx6q based board has been developed and reported in [13] that uses local binary features and EAR for detecting Face landmark and eye state respectively to determine the driver drowsiness. The technique presented in [14] uses the detailed features extracted from eyes, mouth and positions of the head using OpenCV and Dlib library and processes the same to estimate the driver's level of drowsiness. Using a low-cost 3-D sensor, head-pose estimation from iterative closest points algorithm and regions-of-interest (ROI) identification are used for event detection and behaviour analysis by [15]. Microsoft Kinect range camera is used to study the actual movements of driver inside the vehicle including lane changing and lane merging to capture data for driver's attention, fatigue and drowsiness by [16].

The head yaw estimation using nose projected truncated ellipsoidal model provides better visualization for detecting driver distraction as observed in [17]. Based on the eye focus of the driver, drowsiness and distraction are detected using techniques including adaptive boosting and adaptive template matching by [18]. The above technique also uses blob detection to reduce error in detection accuracy of eye region thereby increasing the detection accuracy of eye region and eye states to 99% and 97% respectively. The above technique also detects driver drowsiness and distraction with the success rate of 98%. To monitor driver alertness visual features like eye index (EI), pupil activity (PA) and head pose (HP) are the critical information which provides high classification accuracy, low errors and false alarms as observed in [19]. The driver alertness is monitored by the technique presented in [20] using multiple combination of features and techniques including Haar-like features, block local-binary-pattern features, Kalman filter and Principal Component Analysis (PCA). The above mentioned technique uses PCA for monitoring driver alertness during daytime and block local-binary-pattern features during night time.

Kanade Lucas Tomasi (KLT) algorithm is used for feature tracking from human face by continuously monitoring the video frame. This method is accomplished by finding the parameters that allow the reduction in dissimilarity measurements between feature points that are related to original translational model [21].

In this paper, an Infrared camera is placed in front of the driver to record the behaviour continuously. The collected video is filtered and KLT algorithm is used for face, eyes tracking and detected. Using detect Harris features eye features are extracted to determine the driver state. Finally three classifiers: Support Vector Machine (SVM), k-Nearest Neighbour (KNN) and Ensemble are used for training and testing the dataset. The experimental results presented in this paper suggest that the proposed technique achieves good accuracy in estimating driver hypovigilance detection.

II. PROPOSED METHODOLOGY

The proposed work using image processing for developing a driver hypogilance detection system is shown in Fig 1.

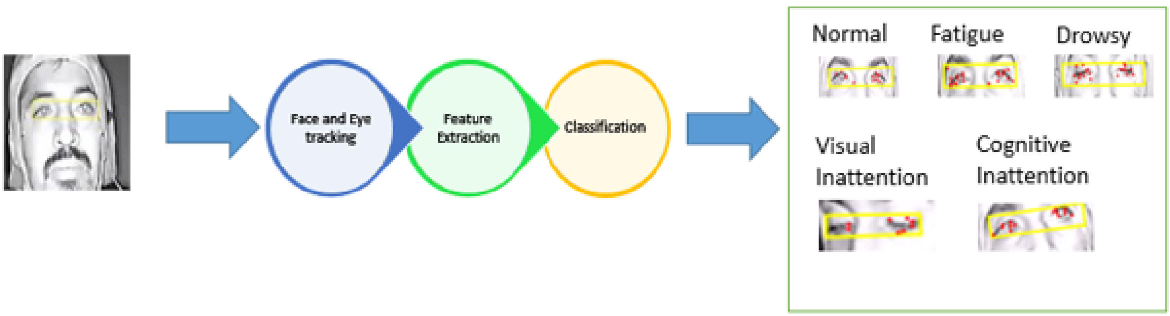


Fig 1 Proposed Methodology for Hypovigilance Detection

Initially behavioural data of the driver is continuously collected using IR camera and processed for face, eye tracking, then extracted eye based features and finally classified into five classes (normal, fatigue and drowsy, visual and cognitive inattention).

III. DATA COLLECTION

The data collection is performed at Artificial Intelligence Research Lab, Chennai. This lab is well equipped with driving simulator with speed dreams game loaded as shown in Fig 2. The game provides a monotonous driving environment with 1-mile oval speedway at constant speed limit of 80 Km/hr. The protocol for the experiment is designed for three different timings (00:00 – 02:00 AM, 03:00 – 05:00 AM and 02:00 – 04:00 PM) from ten healthy subjects.

Fig 2 Data Collection Setup

The total driving session is for continuous two hours with multiple driver behaviour been captured. HIK vision IRPF camera with the video output mode TVI/CVBS/AHD/CVI is placed in front of the driver for this purpose. The actual challenge of this study is to record and monitor the driver behaviour in night vision. The licensed drivers are asked to practice the simulator game initially for ten minutes. From the protocol, when session starts, the driver drives for 15 minutes, during the next 5 minutes, the driver is distracted visually by texting message in mobile, followed by 15 minutes of continuous driving. For another 5 minutes cognitive distraction is induced by asking the driver to answer mathematical questions in phone call, followed by 80 minutes of continuous driving until the driver completely is not able to control sleep.

IV. DATA PROCESSING

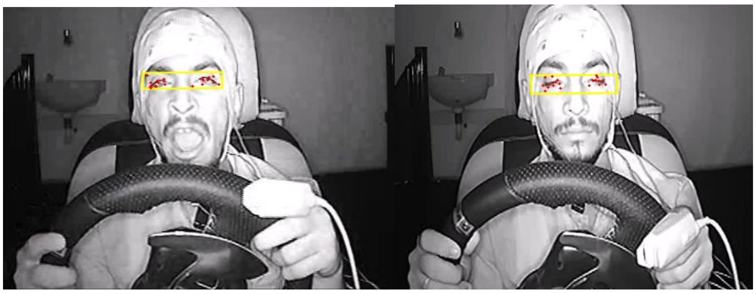
The recorded video has more disturbances that affect the video quality like lightning conditions, position of camera / subject seating. Initially, video frame is tracked for facial features (face, eyes) detection using KLT (Kanade-Lucas Tomasi) algorithm. The Geometric transformation is applied for eye tracking during head rotation, translation and scaling from initial to changeable position.

Table 1 Harris features determined for hypovigilance detection

Driver state	Frame	X value	Y value	area	Eye status
Normal	2018	16.164	7.620	4	
Visual Inattention	7376	12.483	8.906	2	
Cognitive Inattention	8419	7.742	8.506	3	
Fatigue	11287	9.293	7.304	3	
Drowsy	14182	22.123	8.785	0	

The bounding box of eyes uses detect Harris Features to determine eyes open/closed based on the percentage of eye closure (PERCLOS) calculated. Harris features provides three main parameters: total area of the eye portion and the coordinates (x, y) of the location of eye. Similarly, all frames are calculated. Table 1 tabulates the corresponding parameters based on the various driver behaviour. With these features extracted, the driver behaviour is classified as normal, fatigue, drowsy, visual and cognitive inattention. Fig 3 shows the eye detection using Harris features in various driver behaviour.

a) Normal b) Cognitive inattention c) Visual inattention



d) Fatigue e) Drowsy

Fig 3 Eye detection in driver hypovigilance states

V. RESULT

The driver behaviour is classified based on the focus of the driver on road and time taken for eye blink / closing of eye over a long duration. In **normal state** - driver is continuously focused on road with normal eye blinks, **cognitive inattention** – the driver is partially focused, eyes are detected and head is tilted, **visual inattention** – driver is mostly unfocused and eyes are mostly not detected for a short period, **fatigue** - the eyes are detected but half open and **drowsy** – the eyes are completely closed. Based on the area of the eyes which is calculated from Harris features, the driver hypovigilance states have been determined. The three classifiers: SVM, KNN and Ensemble are used to classify the five classes of driver behaviour and the results are shown in Table 2. From Table 2, the Ensemble classifier achieves the highest accuracy of 64.1% in detecting driver hypovigilance.

Table 2 Performance on Image in Driver Hypovigilance Detection

Image Accuracy						
Classifier	**Normal**	**Visual Inattention**	**Cognitive Inattention**	**Fatigue**	**Drowsy**	**Average**
SVM	96.0	8.0	15.2	24	88.0	46.2
KNN	96.0	59.2	45.6	52.8	65.6	63.8
Ensemble	96.0	62.4	44.8	53.6	63.2	**64.1**

VI. DISCUSSION

The challenge in the work on driver hypovigilance detection using behavioural measure is to determine five different behaviours of driver by continuously monitoring the driver during driving. It is understood that the driver cannot immediately change from normal to drowsy state. So, the subject undergoes various stages of drowsiness. They may also be in fatigue state or visually or cognitively distracted. The proposed system can provide an alert for drowsy, fatigue and inattention state by differentiating them and providing alarm based on the priority of emergency. In this system, the driver face and eyes are tracked only if he/she is focused on road. Once the eyes are detected then the Harris features can extract feature parameters for corresponding frames.

Fig 4 shows the comparison on performance of behavioural measure using two and five states of behaviour of the driver, we name it two-class and five-class respectively. From Fig 4, it is understood that two-class detection obtains maximum accuracy of 100% (all classifier) than five-class detection 64.1% (Ensemble). However, to develop a Driver Assistance System, the number of class identified from the driver hypovigilance should be more. On combining the fused physiological measure and behavioural measure, the better performance with maximum accuracy can be produced on driver hypovigilance detection.

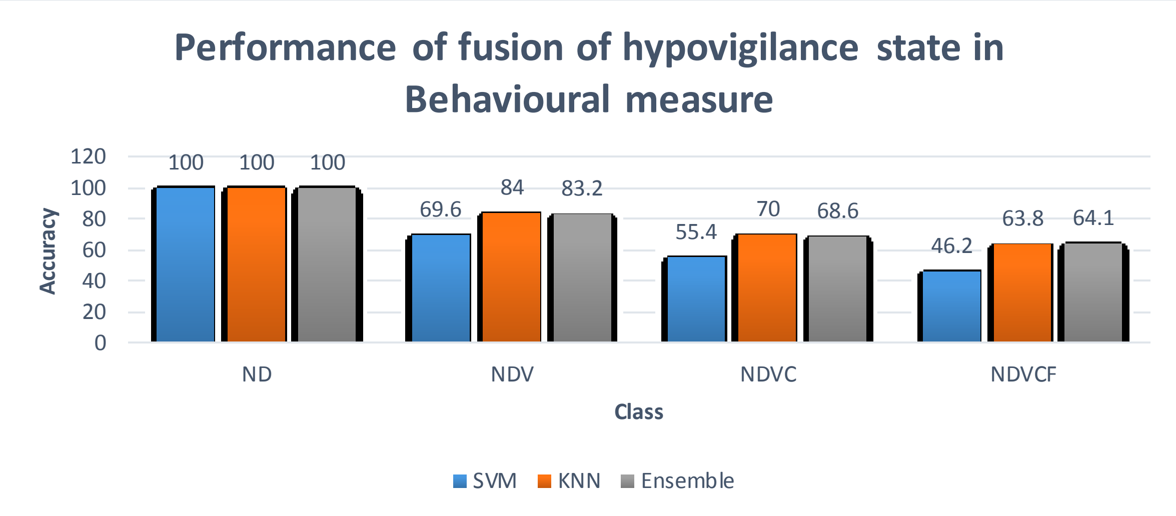


Fig 4 Performance of Behavioural measure

N-Normal, D-Drowsy, F-Fatigue, V-Visual Inattention, C-Cognitive Inattention

VII. CONCLUSION AND FUTURE WORK

Driver Hypovigilance (normal, fatigue, drowsy, visual and cognitive inattention) detection using behavioural measure has proved that on multiple class detection, the average accuracy achieved is 64.1% and for binary class detection the average accuracy achieved is 100%. This work can also include mouth detection for better result. In future, the drivers' hypovigilance can be detected by using physiological and vehicle-based measures along with behavioural measure for providing good performance.

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