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DRIVING PERFORMANCE ANALYSIS AND RISK DETECTION

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ABSTRACT

Several studies have demonstrated that operating an unfamiliar vehicle can potentially present additional risks, particularly for inexperienced drivers. The evaluation, however, may be subjective and constrained because these studies have often employed statistical approaches to analyze collision and near-crash data from various driver groups. We proposed that it would be valuable to take into account the vehicle dynamic signals from the CAN-Bus for a more impartial viewpoint. In this study, 20 drivers took part in an experiment where individual driver behaviour was modeled using a Gaussian model and driving performance was assessed using a dissimilarity score, which is calculated as the square of the Euclidean distance in the space of dynamic features of the vehicle. The findings demonstrate that the difference in driving performance brought on by driver experience and vehicle familiarity (i.e., experienced driver vs. inexperienced driver; familiar with car vs. unfamiliar with vehicle) was plainly seen. Furthermore, we discovered that the brake signal among the signals looked at better captures this variance, which might be employed for advanced car technology to lower collisions and increase road safety. Although it can occasionally be stressful for drivers, parallel parking is thought to be a solid indication of a driver's driving abilities. The time utilised to calculate each driver's completion time for the parallel parking challenge comes from their third attempt, indicating that they are already comfortable with the car and the road. We can observe that experienced drivers, who often do better behind the wheel, take less time overall to complete this activity. One of the most crucial driving abilities is the ability to perceive possible accidents and take the appropriate precautions. An accurate risk perception model and evaluation can efficiently pinpoint driver perception weaknesses and act as a crucial human aspect in the development of advanced driver assistance systems. It is challenging to quantify the assessment of perception abilities using standard methods since they typically rely on macroscopic statistics results and lack useful mathematical models.

CHAPTER 1 INTRODUCTION

According to data on auto accidents, 90% of all crashes are caused by driver error, and drowsy driving accounts for a significant portion of those errors. Systems that keep an eye on the driver's condition, in particular danger factors like drowsiness are necessary for this reason. By providing a warning at an early stage of intoxication, these technologies have the potential to improve traffic safety. Since automated driving is designed to minimise or possibly completely eliminate human-based errors, it is anticipated that it will have a significant impact on road safety. Yet, according to the SAE's taxonomy, the automation of the driving task is a multi-stage process that ranges from manual driving (SAE level 0) through total automation of the driving activity (SAE level 5).

Yet, according to the SAE's taxonomy, the automation of the driving task is a multi- stage process that ranges from manual driving (SAE level 0) through total automation of the driving activity (SAE level 5). Driver fatigue continues to be a significant factor, particularly in SAE levels 1-3 where the driver forms the automated system's "allback level" and is required to always be able to assume full control within a reasonable amount of time. Moreover, the danger of falling asleep while driving grows more quickly due to the decreased active involvement in the job. Systems that can accurately identify driver intoxication are therefore required

1.1 MOTIVATION

Nowadays, transportation infrastructure is crucial to human activity. Any of us can become sleepy while driving, whether it's from getting too little sleep the night before, a physical condition change, or lengthy travel. The feeling of sleep lowers the driver's degree of alertness, resulting in hazardous conditions and raising the likelihood of an accident. One of a person's essential needs is sleep. Without enough sleep, the body reacts slowly, diminishing both awareness and reaction time. It also results in low alertness and concentration problems, which make it harder to do activities requiring care, like driving a car. One of the major contributing factors to accidents on the road is driver weariness and drowsiness. Globally, they increase the number of fatalities and injuries every year. As a result of these issues, the driver sleepiness detection alarm system was developed.

CHAPTER 2

LITERATURE SURVEY

[1] An enhanced driver's risk perception modeling based on gate recurrent unit network by Kazuya Takeda, Peng Ping; Weiping Ding; Yongkang Liu has been added to the proposed system.

Here the risk perception model based on traffic scene knowledge can precisely anticipate the actual cognitive behaviour of each driver by validating the classification performance on several drivers. Also, the suggested GRU-based approach surpasses the established machine learning algorithm in simulating the behaviour of the driver's risk perception. It is challenging to quantify the assessment of perception abilities using standard methods since they typically rely on macroscopic statistics results and lack useful mathematical models. To do this, this paper uses a deep learning-based semantic segmentation technique to first establish a semantic understanding of traffic situations. The results of the driver's risk perception are then combined with the semantic understanding information to create a time series of data that reflects risk perception ability. Lastly, we develop a behavioural model that responds to the driver's capacity for risk perception using a gate recurrent unit (GRU) network-based learning framework.

[2] Driving Behavior Aware Caption Generation for Egocentric Driving Videos Using In-Vehicle Sensors by Hongkuan Zhang; Koichi Takeda; Kento Ohtani; Ryohei Sasano; Yusuke Adachi has been added to the proposed system.

Here According to the contents of the film, video captioning attempts to produce textual descriptions. In order to provide proper insurance coverage, especially for newly emerging MaaS businesses, an insurance firm must now assess the risk associated with autonomous driving vehicles. The insurers must examine a vast amount of driving data, including dash cam footage and sensor signals, to evaluate the risk of autonomous driving business plans with a defined path. Creating captions for driving films can help insurers grasp the video's contents more quickly and streamline the process. As there are no ego vehicles in these egocentric movies, it is impossible to ground explanations of latent driving behaviours in specific visual cues, which is a natural challenge with driving video captioning. We propose to use in- vehicle sensors that store data on driving behaviour to help with caption creation in order to focus on producing driving video captions that accurately describe driving activity. We test our method using a dataset of driving video captions from Japan called City Traffic. The results show how in-vehicle sensors can improve the performance of generated captions overall, particularly when it comes to producing more accurate descriptions for driving actions.

[3] Cooperative Detection Method for Distracted and Fatigued Driving Behaviors With Readily Embedded System Implementation by Feng Zhang; Junjie Wang; Yangkun Wang;Xiaodong Yu; Yi Dai has been added to the proposed system.

Here It is important for safety reasons to promptly and accurately identify these behaviours in order to reduce the risks brought on by distracted and fatigued driving. The interaction of various distracted and fatigued driving behaviours among the state-of-the-art detection methods based on in-car image analysis may render certain behavior-targeted detection ineffective and unreliable, while the complex neural network-based detection methods may be difficult to interpret and impractical for hardware implementation. In this paper, a novel cooperative detection approach for fatigued and distracted driving behaviours is proposed, taking into account the method's overall performance, operational complexity, and hardware implementation. Investigated are the key indicators for hand- held calling, continuous left-right eye movement, yawning, eye closure, and the cooperative relationship between various actions. On the established dataset, which includes photos of genuine cockpit driving scenarios with multiple drivers in varying lighting and backdrop conditions, experiment cases are run. For the tested behaviours via support vector machine (SVM) on a PC platform, the suggested technique achieves over 98% detection precision and 37 frames/s processing speed on the established Di Fa C Tes dataset. The article also includes a hardware assessment of the suggested approach on the i.MX 8QuadMax platform, which achieves processing speeds of 16 frames per second with precision of over 96.8%. The experimental outcomes show that the suggested approach is useful in accurately and quickly detecting distracted and fatigued driving behaviours, and they also point to the possible embedded system applicability.

[4] Performance Analysis of SSD and Faster RCNN Multi-class Object Detection Model for Autonomous Driving Vehicle Research Using CARLA Simulator by Mohana; DR Niranjan; BC VinayKarthik has been added to the proposed system.

Here In order to develop safe and capable self-driving systems, research into autonomous vehicles has developed tremendously over time. At the same time, legal authorities are looking into measures to reduce the risks that these completely driverless vehicles pose. These developments may lead to significantly safer conditions for commuting, fewer accidents, and even the abolition of the need for human drivers. Current advancements in the field demonstrate that using object detection models in conjunction with an on-vehicle camera module offers greater accuracy and resilience than using RADAR or LiDAR. Using a variety of performance criteria, this research suggests two object identification algorithms for autonomous driving applications: SSD and Faster RCNN. To create synthetic data to train and test the models, CARLA Simulator was employed. Findings indicate that SSD has a mean Average Precision (mAP) value of 88.998% while Faster-RCNN has a mAP of 94.32%. Faster-RCNN, on the other hand, had a speed of 106 ms/image while SSD only had a speed of 30 ms/image. It was concluded that the SSD technique is significantly more suited for this problem when taking into account the real-time and speed limits in autonomous driving because the accuracy gap between the models was relatively smaller than the calculation speed gap.

[5] Distracted Driving under Angry: A Study on Driving Performance Analysis and Risk Detection by Chengmou Li;Gang Guo; Hao Chen; Juncheng Zhang; Yinghao Zhong; Yingzhang Wu has been added to the proposed system.

Here Driving risk status is significantly impacted by driver rage and distraction. For the intelligent transportation system, it is important to investigate the driving danger state. Uncertainty still exists regarding the mechanism of driving danger in various emotional and distracted states. This article explores changes in driving risk caused by various driver distractions and emotions. By the use of the driving simulator, two distraction tasks (a music task and a two-level cognitive distraction task) were created. With the data being recorded, 24 drivers operated their vehicles

in a fictitious metropolitan setting. The risk compensating mechanisms as well as the lateral and longitudinal manipulation behaviours were examined. The probability distribution of driving risk under various distracted and emotional driving conditions was examined using K-means clustering. To determine the driving risk, three classification models—deep neural networks (DNN), k-nearest neighbour (KNN), and support vector machines (SVM)—were employed. The findings suggest that driving under the influence of anger will only become worse. It will, nevertheless, focus the driver's attention. The high risk probability of high-level cognitive distraction was lower than the low-level in the two-level cognitive distraction tests. The driver state management system in the smart cockpit may advance as a result of the accuracy rate of the driving risk state recognition model based on DNN reaching 0.908 at the same time.

[6] Automatic detection of drowsiness in EEG records based on time analysis by Amit Prasad; Ishita Dey; Gahana Rao; Shivansh Jagga; A. Sharmila; Siddharth K Borah has been added to the proposed system. Here Almost 20% of accidents that result in injuries and fatalities worldwide have driver tiredness as their primary contributing factor. Driver performance and vehicle handling skills suffer as a result of sleepiness. This study tries to automatically identify the level of sleepiness in EEG records by applying time analysis techniques. The band-pass filtering with a cut-off frequency of 0.5 Hz to 60 Hz was used to reduce noise from the EEG signals before segmenting them into 5 second intervals. To distinguish between the awareness and drowsiness stages, three characteristics were computed on a single EEG channel. Up to 85.7% of alertness and sleepiness are correctly detected using this method. Based on the parameters and the data, both stages can be distinguished. It is accessible and real-time outputs are possible. These parameters can be used to implement an autonomous sleepiness detection system in automobiles, reducing the risk caused by drowsy driving. Using samples taken from The MIT-BIHPolysonographic Database on physionet.org,the algorithm created here was evaluated.

[7] On the Development of an Acoustic- Driven Method to Improve Driver's Comfort Based on Deep ReinforcementLearning by Erickson R. Nascimento; Gregorij Kurillo; Isabella Huang; Ismael Villegas; Michal Gregor; Ruzena Bajcsy hasbeen added to the proposed system.

Here our expanded understanding of driver modelling and behaviour prediction has helped to increase the safety and comfort of drivers throughout the years. The number of methods that see the passengers and the vehicle as parts of a dynamical vibro-acoustical system is notably lacking despite these great advancements in autonomous and interactive systems. Vehicle sound can have a significant impact on the driver's performance, concentration, and comfort in addition to providing information about the environment and the condition of the vehicle. This study intends to examine how psychoacoustic annoyance (PA) measurements and perceived vehicle sounds interact. By using acoustic-driven learning, we hope to develop an intelligent agent that would act to make driving more enjoyable. The study provides a reinforcement learning system that learns from the environment, i.e., the vehicle interior, to address the issue of selecting the appropriate behaviours to reduce acoustic nuisance. In order to lessen the driver's acoustic discomfort, the approach actively alters the state of the car (e.g., closing or opening the window and selecting the cruising speed). The study's findings, which were produced using the GTA V simulator, demonstrated that the trained agent had mastered the necessary steps to lower PA measures. The research also makes available to the public a brand-new multi-modal dataset made up of multiple trips in a real car and a thorough examination of how the signal from the car affects acoustic discomfort.

[8] IOT Based Smart Vehical Monitoring and Tracking System by Alok Agarwal; Megha Dewan has been added to the proposed system.

Here Automobile accidents are considered to be one of the most harmful events. Although there are many distinct factors that contribute to auto accidents, driver negligence and irrational speeding are the main causes of injuries. Due to the loss of awareness, it also appears that it is difficult to reach the accident site in a timely manner. In order to decrease accidents and avoid theft, smart vehicles incorporating Internet of Things (IoT) technology are the answer. This research provides clever system architecture to swiftly identify the accident. The ultrasonic sensor used by this system continuously measures the distance between the vehicles. The suggested design is aware of GPS/GPRS and GSM, which immediately transmit an alarm message to nearby emergency responders and family members. The GPS/GPRS system can be employed in the event of an accident or theft and continuously monitors the location ofthe car.

[9] Young Drivers and Their Risky Behavior on the Roads by Alica Kalasová; Ambroz Hajnik; Kristian culík has been added to the proposed system.

Here the most expensive thing is a human life. However, more than 25,000 people perish in traffic accidents every year in the European Union. The general statistics on road accidents in EU nations are provided in this article. Additionally, it concentrates on particular data regarding the quantity of traffic accidents in Slovakia that are caused by young drivers. On the roads in the Slovak Republic, the motorist poses a risk to other road users regardless of their age or level of driving expertise. In order to learn more about the peculiarities of young drivers' driving behaviour, a survey was carried out. This paper contains the survey's findings. These findings were utilised to identify typical risky or other driving behaviour among young people. A list of significant steps to increase the safety of young drivers in traffic can be found at the article's conclusion.

[10] Road Condition Detection using Adaptively Chosen Deep Learning Model and Precautionary Special-Guidance for Driver-Safety by Md Masum Billah; Nilanjan Chattaraj has been added to the proposed system.

Here using a comparison of image processing and different Deep Learning algorithms, an integrated pattern recognition model is developed to prevent fatal accidents caused by potholes, damaged roadways, and speed bumps. The system seeks to select the best model from among ResNet50, Efficient Net B7, VGG16, and Alex Net by processing road photos in real- time and taking speedometer data into account while weighing the trade-off between model efficiency and prediction time complexity. To stress human safety, this adaptive selection procedure of DL algorithms with the vehicle's speed is used. The GPS coordinates of the road map and a dynamic time-dependent variable linked to the volume of traffic on that route will also be used to identify the designated bad roads. This integrated model may provide real-time preventative warnings not just during the day, but also at night, in foggy or hazy conditions, when visibility is reduced.

CHAPTER 3 EXISTING SYSTEM

In the existing system the driver performance and risk factor will be evaluated by fatigue analysis. Because of the nature of the issue, no nation in the world has fully addressed fatigue as a safety issue. Unlike to alcohol and drugs, which have obvious key signs and tests, that are simple to obtain, fatigue is generally quite difficult to measure or detect. The best ways to address this issue are probably to raise awareness of incidents linked to driver drowsiness and to encourage drivers to admit it when necessary. The latter cannot be accomplished without the former because driving for extended periods of time is very lucrative, while the former is difficult and far more expensive to do. A physiological state with a propensity to nod off is drowsiness. Strictly speaking, drowsiness differs from weariness, which is the inability to continue doing the same thing. Tasks that are consistently performed in the same manner with the same muscle groups and at a high repetition rate—often while adopting forced postures like staring at a screen—leadto fatigue.

3.1 DISADVANTAGES OF EXISTINGSYSTEM

- The existing system does not produce good results in low lightconditions.
- If the light conditions are dark or toolow it is unable to detect the face andeyes of the driver which results in lower accuracy.

CHAPTER 4 PROPOSED SYSTEM

The proposed system will define the driver performance Based on quantifiable variables that are gathered experimentally, sleepiness detection using patterns analysis is generated. These factors can include the vehicle's path in the traffic lane, speed, acceleration, braking, gear shifting, and hand pressure on the steering wheel. This method's drawback is that each car's attributes and each driver's unique driving style are taken into account when modelling results. The states of the drivers can be identified by using image processing. If the driver is awake or sleepy, it may be determined from the face image. The fact that the motorist is attempting to close his eyes indicates that he is drowsy. This technique can be utilised with techniques like the template pairing technique, where a driver template is established, and has the benefit of not being obtrusive. In order to calculate the rate of drowsiness, the technique of eye behaviour measures how frequently the eyes blink and how long they remain closed.

4.1 ADVANTAGES OF PROPOSEDSYSTEM

- Controls accident range due to driverdrowsiness to 90%.
- High accuracy by using Haar cascade for the detection of driverfatigue.
- Not create uncomfortableenvironment for drivers

CHAPTER 5 MODULES DISCRIBTION

5.1 MODULES

- Video access
- Face Extraction
- Eye Blinking Extraction
- Time variation
- Driver alert

MODULES DESCRIPTION

5.2.1 VIDEO ACCESS

The system's primary goal is to enhance the thermal imagers' movies and provide them the capacity to acquire, stream, and analyse videos. A video capture unit and a video processing unit will be built in the FPGA's PL portion. For the purpose of processing the driver's weariness, the driver picture video is retrieved.

5.2.2 FACE EXTRACTION

The algorithm used by OpenCV to extract faces. It is not a smart idea to identify or detect both eyeballs in the original image due to the complicated background; doing so would need us to spend a lot more time exploring the entire window with subpar results. First, we will identify the face and narrow the detection window for both eyes. By doing this, we may increase tracking accuracy and speed while minimizing the impact of a complicated background. Also, we provide apowerful yet really easy way to lessen the complexity of computation.

5.2.3 EYE BLINKING EXTRACTION

The video is divided into frames, and then each frame is individually processed. The Viola-Jones algorithm is used to

identify faces in frames. Then, a cascade classifier is used to extract from the face the necessary features, such as the eyes, lips, and head. Rectangles on the face represent the area of interest. The primary indicator of drowsiness in this case is decreased eye blink frequency, which typically ranges from 12 to 19 times per minute and signals drowsiness. Average sleepiness is calculated rather than eye blinking. Non-zero values represent partially or fully open eyes, whereas zero represents the detected eye (closed eye).

5.2.4 TIME VARIATION AND DRIVERALERT

We must continuously track the faces for any type of distraction because the project is real-time. So, throughout the entire time, faces are continuously detected. Driver drowsiness face detection is classified according to the difference in time variation. The driver's face is continuously watched for any unusual movements in the face tracking module. Also, the system is notified of distraction by the driver's extended, unblinking gaze, which can be interpreted asa lack of focus.

5.2.5 DRIVING PERFORMANCEANALYSIS

The evaluation of a driver's driving performance being very subjective, we continued to operate under the presumption that theoretically, good, safe, or convenient driving should be reflected with stable, steady, or low-variance vehicle dynamical data. A skilled driver should also behave in the "good driving" zone for the most of the time, although "poor driving" may happen for a brief period of time due to visual or cognitive inattention, unfamiliarity with the route, being preoccupied with other tasks, etc. is what the second premise in this part isbased on.

CHAPTER 6 ALGORITHMS AND METHODS

The two main methods algorithm used inthis paper are

- Eye blink detection
- Harr cascade algorithm

6.1 EYE BLINK DETECTION

We can use facial landmark detection to pinpoint crucial facial features Including the eyes, brows, nose, ears, and Mouth. This indicates that by knowing the indexes of the various face sections, we can extract particular facial structures. We are

only interested in two sets of facecomponents for the purpose of blink detection—the eyes.

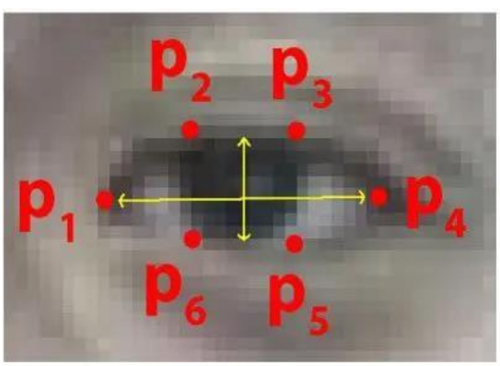

Fig 6.1 Eye blinking variation

Six (x, y)-coordinates are used to symbolise each eye, beginning at the left corner (as if you were staring at the subject) and moving clockwise around the remainder of the area.

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

Where the points p1,..., and p6 are2D facial landmarks.

This equation's denominator, which is weighted correctly because there is only one set of horizontal points but two sets of vertical points, computes the distance between horizontal eye landmarks while the numerator computes the distance betweenvertical eye landmarks.

6.2 Harr cascade algorithm

Face detection is a topic with many applications that is very popular. Current smart phones and laptops have face detection software built in that can verify the user's identification. Several apps have the ability to capture, detect, and process faces in real time while also determining the user's age and gender and applying some really amazing filters. The list includes more than just these mobile apps because face detection has numerous uses in surveillance,security, and biometrics.

Allowing multiple scale (Multiple size)detection faces = face_cascade.detect MultiScale(gray, 1.1, 6)

#Creating Rectangle around facefor(x, y, w, h) in faces:

cv2.rectangle(img, (x, y), (x+w, y+h), (0, 0,250), 2)

#Displaying the image cv2.imshow('Detected Face Image', img) #Waiting for escape key for image to close cv2.waitKey()

CHAPTER 7 EXPREMENTAL ANALYSIS

The influence of the driver's experience can also be shown when the other moves are examined in greater detail. The brake event in Figure 3 serves as an illustration of how the brake pedal position varies between two groups of braking events that occur at the same place. We can see that an experienced driver makes smoother brake actions, but a beginner driver makes maneuvers that are more variable and require repeated adjustments, which is uncomfortable for the passenger. Among our group of experienced drivers, we chose two at random who had eight or more years of driving experience and were well-known forbeing safe drivers.

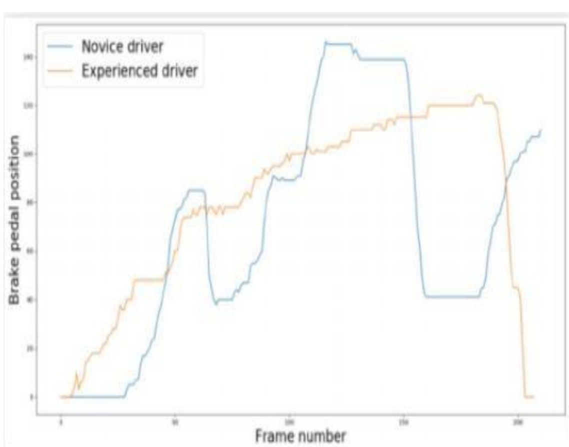

Fig 7.1 speed performance of driver

To determine how distinct they are from every other driver, we summed their data and used them as a baseline. For each driver group and event type, we generalize the driving performance using Gaussian models in the vehicle dynamical feature space. The Euclidean distance squared between the models is used to get the dissimilarity score. We propose that the driver's behaviour is comparable to our baseline "good driver" when the distance is little and the dissimilarity score is low, hence the driver should exhibit improved driving performance.

CHAPTER 8 FUTURE ENHANCEMENT

In future the performance of driver can be elaborated although the range of the features examined in this study is constrained, it is worthwhile to investigate additional feature combinations and combine IMU data from smart phones for analysis of other variables that may define driving performance, such as weather, daylight, traffic, and distraction scenarios. In order to develop smart decision modelling procedures for advancements in intelligent vehicles, it is also worthwhile to establish baselines using chosen good driving behaviour and test them in the real world. This is made possible by the increased availability of naturalistic driving data.

CHAPTER 9 CONCLUSION

In this study, we investigated individual driver behaviour by modelling it using a Gaussian model and examined the dissimilarity between their performance and

a baseline of an experienced driver. Based on the driver's experience and familiarity with the vehicle, a variation in driving performance was exhibited. Also, we discovered that the brake signal may more accurately describe this variation among the signals we looked at. Therefore, it is recommended that brake data dynamics be captured and modelled to indicate whether the driver is experienced enough to fully turn on certain driver-assist systems, thereby preventing potential accidents and increasing overall safety. This will allow advanced vehicle systems to determine whether the current driver is familiar with this specific vehicle.

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