Human Driving Behavior Detection System: A Comprehensive Survey

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Abstract: *Driving behavior is the manner by which drivers respond to actual driving environments and a major factor for road traffic safety. There are many research studies contributing to detection of driving behavior that may cause traffic crashes. According to the statistics of road accidents from the year 2010 to 2019, the car and taxi type of vehicles shows about nearly 25,00,000 cases of road accidents. It keeps increasing every year and by the year 2019, it shows that the number of road accidents recorded are nearly 5,00,000. The proposed method uses the visual data in order to extract features such as orientation and speed of the vehicle, alcohol and smoke detection of a driver along with the temperature range.*

Keywords: *Behavior detection, Sensor data, Driving behavior, Vehicle motion data, Human Inattentive Aggressive Driver Behavior.*

I. Introduction

Road accidents are undoubtedly becoming a growing concern leading to causes of death and injuries. Major causes of accidents occur due to human errors. As society develops, the number of vehicles on the road increases and the driving environment becomes increasingly complex. Majority of accidents occur due to over speeding. If given a chance, man is ready to achieve infinity in speed. Increase in speed increases the risk of accident and severity of injury during accidents. Faster vehicles are more prone to accidents than slower one and the severity of accidents are high. The ability to judge the forthcoming events also gets reduced while driving at faster speed which causes error in judgment and finally accidents.

Many studies related to safe driving have been performed. Some examples include systems such as intelligent transportation system (ITS) and advanced driver assistant system (ADAS) which assist in driving by performing additional safe driving functions. Technologies that are currently under active research and development include forward collision warning (FCW), lane departure warning (LDW), and pedestrian detection systems (PDS). Many unclear definitions of aggressive driving behavior still exist. Among them, the definition of aggressive driving by National Highway Traffic Safety Administration (NHTSA) is 'a driving method that endangers or tends to endanger personal and property safety'. And Tasca proposes a definition that, 'A driving behavior is aggressive if it is deliberate, possible to extend the chance of collision and is driven by impatience, annoyance, hostility and/or an effect to avoid wasting time'.

Considering that many previous studies on aggressive driving behavior do not focus on abnormal behavior during driving, but on the whole driving process, this paper attempts to pay more attention to unusual behaviors. Aiming at the identification of driving behaviors, we are able to divide the driving behavior into two sorts. One is continuous behavior, such as over speeding. The observed indicators remained stable for a period. It must be determined by a certain threshold whether the state is abnormal or not.

In existing driver behavior analysis systems, the machine learning concept is used in autonomous cars. But this method seems to be difficult because of complex algorithms, and it needs larger samples. However, bound forms of aggressive driving behaviors, such as threatening lane changes, are tough to detect using these algorithms. Certain applications such as user-specific insurance require only vehicle operation information. In the existing driver behavior analysis systems, the motive force directly influences the results of the driving behavior analysis. Therefore, existing systems are not compatible with other application systems.

The proposed systems use gyroscope sensors to acquire the speed and acceleration information of the vehicle and detect dangerous driving behaviors, such as sudden starts or stops. It periodically transmits vehicle operation information to the server and also analyzes the information. When certain dangerous driving behaviors are detected, buzzer alerts the driver. Here, the findings of the sample test offer insights of drivers with aggressive driving behavior.

II. Literature survey

[1] Using Asymmetric Theory to Identify Heterogeneous Drivers Behavior Characteristics Through Traffic Oscillation- This paper applies the asymmetric driving theory to capture driving characteristics of car-following behavior throughout traffic oscillation. The disadvantage is that it seems to be complex because of machine learning algorithms, which is difficult and it needs larger samples.

[2] The Influence of Different Factors on Right-turn Distracted Driving Behavior at Intersections Using Naturalistic Driving

Study Data **-** The proposed method senses the driver's behaviour in the state of drowsiness, it gives an alert. The disadvantage is that more accuracy is needed for the implementation of signs for ADAS.

[3] A Survey on State-of-the-Art Drowsiness Detection Techniques- This paper presents a comprehensive analysis of the existing methods of driver drowsiness detection and presents a detailed analysis of widely used classification techniques in this regard. Thus this method is done by using Top supervised learning, but the method seems to be not accurate.

[4] Video-Based Abnormal Driving Behavior Detection via Deep Learning Fusions. In this paper, deep learning fusion techniques are emphasized, and three novel deep learning-based fusion models are introduced, to fulfill the video-based abnormal driving behavior detection task for the first time. The disadvantage here is it can be used only in autonomous cars.

[5] An Adaptive Batch-Image Based Driver Status Monitoring System on a Light weight GPU-Equipped SBC. Also, the system works with PydMobileNet, which has lower parameters and FLOPs than MobileNetV2, for facial behavior recognition. Hence this method is more efficient and robust and requires less time but the disadvantage is that the Cost is higher and accuracy is less.

[6] Integration of Ensemble and Evolutionary Machine Learning Algorithm for Monitoring Diver Behavior Using Physiological Signals. In the initiative , the performances of the K-nearest neighbors (KNN), support vector machine (SVM), and naive Bayes (NB) algorithms are improved using bagging, boosting, and voting ensemble learning techniques. Here the disadvantage of this proposed method is , very less loss of Mortality .

[7] Real Time Driver Fatigue Detection SystemBased on Multi-Task ConNN.In this article, a Multitasking Convolutional Neural Network (ConNN).With the proposed Multi-taskConNN model, unlike the studies in the literature, both mouth and eye information are classified into one model at an equivalent time. The time taken for the process and displaying the result is much higher which is the disadvantage here.

[8] AI for vehicle behaviour anticipation: Hybrid approach supported Manoeuvre classification and trajectory prediction. This paper proposes a hybrid approach to neural networks and trajectory prediction using Long Short-term Memory (LSTM) and Next Generation Simulation (NGSIM) public dataset that provides real driving data. The disadvantage here is the high cost of implementation.

[9] Driving Behavior Using DeepLearning: Recent Advances, Requirements and Open Challenges Detecting Human Driver Inattentive and Aggressive. In this paper, first they classify and discuss Human Driver Inattentive Driving Behavior (HIDB) into two major categories, Driver Distraction (DD), Driver Fatigue (DF), or Drowsiness (DFD). Here the disadvantage is that it is not much accurate.

[10] A Hybrid CNN framework for behaviour detection of distracted drivers **-** In this paper, presentation of a hybrid CNN framework (HCF) to detect the behaviors of distracted drivers by using deep learning to process image features is done. This system detects whether the driver follows traffic rules or not.The disadvantages of CNN models is classification of images with different positions. Another minor disadvantage is performance.

[11] Determination of Risk Perception of DriversUsing Fuzzy-Clustering Analysis for Road Safety. A driver classification discriminant model was constructed based on Fisher discriminant analysis.Find risks of the driver easily.Reception of experiment is needed for acquiring accuracy is the disadvantage of the paper.

[12] Dynamic Bayesian network approach to evaluate vehicle driving risk based on-road experiment driving data.In this work, they utilize a dynamic Bayesian network for an inferential analysis of driving-related risks based on our assessment of real-world driving data. The disadvantage is that it has complex algorithms.

[13] Detecting Human driver Inattentive and aggressive driving behavior (HIADB) using deep learning. After describing the background of deep learning and its algorithms, presentation of an in-depth investigation of most recent deep learning-based systems, algorithms, and techniques for the detection of Distraction, Fatigue/Drowsiness, and Aggressiveness of a human driver. It requires a really great deal of knowledge so as to perform better than other techniques.

[14] Driving range parametric analysis by interior static magnet motors of electrical vehicles driven considering driving cycles. This paper presents a parametric analysis of the golf range by V-type interior static magnet motors of electrical vehicles driven aiming at maximum golf range . This shows that both for driving cycles, an equivalent parameter may need different influences on the energy consumption of the motors of electrical vehicles.

[15] Driving Stability Analysis Using Naturalistic Driving Data With Random Matrix Theory. This method can extract features, based on the random matrix theory, to reflect the statistical difference between actual driving data and the data that would be generated by a theoretically ideal driver. Using the extracted features, a driving behavior analysis application that partitions drivers into clusters to spot common driving stability characteristics is demonstrated and discussed.

[16] Visualization of driving behaviour based on hidden feature extraction by using deep learning. Based on the DSAE, they propose a visualization method called adrivingcolor map by mapping the extracted 3-D hidden feature to the red green blue (RGB) color space. It shows the driving color map based on DSAE facilitates better visualization of driving behavior.

[17] Bias Remediation in Driver Drowsiness Detection Systems Using Generative Adversarial Networks.The framework improves CNN, trained for prediction by using Generative Adversarial networks for targeted data augmentation supported a population bias visualisation strategy that groups faces with similar facial attributes and highlights where the model is failing. The proposed framework isn't limited to the driving force drowsiness detection task, but is often applied to other applications.

[18] Driving conditions of new energy logistics vehicles using big data technology. The research here is based on an actual project of an automobile manufacturing company, consulting a large amount of relevant domestic and foreign literature. Based on the constructed new energy truck driving condition analysis model, big data technology was used to perform a big data analysis experiment on the actual operation data.

[19] Analysis of road-user interaction by extraction of driver behavior features using Deep Learning. In this study, an improved deep learning model is proposed to explore the complex interactions between the road environment and driver's behaviour throughout the generation of a graphical representation. The graphical outcomes reveal the method's ability to efficiently detect patterns of simple driving behaviors, as well as the road environment complexity and some events encountered along the path.

[20] An Effective Bio-Signal-Based Driver Behavior Monitoring System Using a Generalized Deep Learning Approach - Therefore, in this paper, a bio-signal-based system for real-time detection of aggressive driving behaviors using a deep convolutional neural network (CNN) model with edge and cloud technologies is carried out. Moreover deep learning requires hundreds of machines. This increases cost to the users.

[21] A Comparative Study of Aggressive DrivingBehavior Recognition Algorithms Based On Vehicle Motion Data. The objective to reduce traffic accidents and improve road safety, effective and reliable aggressive driving recognition methods, which enables the development of driving behavior analysis and early warning systems, are urgently needed. The disadvantage here is that the weight of each feature data set is much higher which is because of complex machine learning algorithms.

III. Existing system

In the existing system, a bio-signal-based system for real-time detection of aggressive driving behaviors using a deep convolutional neural network (CNN) model with edge and cloud technologies. The system consists of three modules, which are the driving behaviors detection module, the training module, and the analyzing module connected with a telecommunication network. The DCNN model of this system is evaluated using a holdout test set of 30% on two different processed bio-signal datasets. However, it requires a light-weight detection module and a strong training module with real-time storing and analysis of drivers behaviors data.

IV. Proposed system

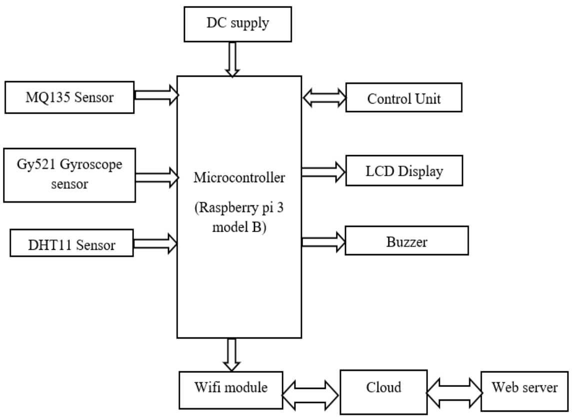
In the proposed method, the device collects real-time vehicular sensor data, such as acceleration, lateral orientation, angular velocity, motion of objects and monitors the alcohol level of the driver. However, with the sensing technology, the data collection raises severe privacy concerns among users who may perceive the continuous monitoring by the operator as intrusive. The work flow of Driving Sense is mainly divided into three components:

1. Data collection.

2. Data processing.

3. Dangerous driving behaviour identification.

For data processing, Driving Sense first determines the sensor error distribution. For data collection, control units and Wi-Fi modules are used. Speeding is identified by comparing the estimated speed with the predefined speed obtained from a navigation system. As a result, the findings of the sample test offer insights into the effects of drivers with aggressive driving behaviour and the user can access those data for future reference.



V. Conclusion

The systematic review provides details of behavioral, vehicular and physiological parameters based driver detection techniques. These techniques are elaborated intimately and their pros and cons also are discussed. The comparative analysis showed that none of those techniques provide full accuracy, but physiological parameters-based techniques. provide accuracy in various situations.

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