

Early Distracted Driving Detection from Smartphone Audio Signals

R Angeline, Anshul Bhargava, Santhosh P, L Alikhan, Ashar SK

Abstract: *In most of the road accidents cases registered, the prime cause always revolves around distracted driving. Distracted driving comprises of four types of driving events: Fetching Forward, Eating or Drinking, Turning Back, Picking Drops. This problem can be resolved by predicting the driver's behavior and take preventive actions beforehand. To make this into reality, we have used concepts of deep learning. It use the recorded audio signals from the driver's cellular devices, these signals are created during any of the above driving event occurs. It convert them into a frequency-time profile and then pass them to a classifier, which classifies them into four mentioned driving events based on that preventive measure could be taken.*

Index Terms: distraction, driver state, in-vehicle signal, unsupervised learning, and supervised learning.

I. INTRODUCTION

Distracted driving is one of the main factors in the present street mishaps. The number of drivers who were associated with distracted driving were 660,000 every day. Most drivers neglect to acknowledge themselves as distracted while driving. Distracted driving perceived robustly and precisely. Hence distracted driving ought to be perceived when possible. Researchers have observed that distracted driving conduct impacts audio signals and different distracted driving practices sway audio signal frequency differently. To overcome this issue, a distracted driving conduct recognition system be implemented when possible, which anticipates potential fender. There are existing examinations using which distracted driving propensities identified by pre-conveyed foundation, for example, cameras, infrared sensors and other EEG devices, which brings about staggering expense. Lately, with expanding fame of smartphones, executing such ER systems made possible, financially attainable and convenient, utilizing sensors like gyroscope, accelerator and camera. Our principle objective is to fabricate an ER system for Distracted driving utilizing smart phones.

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II. RELATED WORK

Existing studies have shown that irregular driving practices include distracted, drowsy and drunk driving. These studies recognize driver's status depending on pre-deployed foundation, for example, infrared sensors, camera and EEG devices, bringing about surprising expense. Existing system quantitatively assess driving styles by normalizing driving conduct dependent on customized driver modeling. The arrangements all depend on pre-deployed framework and extra equipment that acquire establishment cost. Besides, that extra equipment could endure the distinction of day and night; terrible climate condition and high support. The information from these equipment is once in a while not extremely precise. Investigates on traffic security demonstrate that the connected statistical modeling fizzles when managing complex and profoundly nonlinear information, recommending that the connection between the impact factor and crash results is perplexing than can be examined by a solitary statistical approach. With expanding use of smart telephone, different smart telephone based applications are created to distinguish driving practices utilizing sensors installed in smart phones, for example, quickening agent, whirlygig, and camera. Among the most unsafe sorts of driving, distracted driving tops the outlines. There have been different endeavors to make identify these driving conduct utilizing Smartphone sensors. With the information gathered from our writing overview, we note the accompanying phases of this application advancement utilizes back cameras of smart phones to screen street conditions, though use double cameras of smart phones to tract street conditions and recognize drivers' status in the meantime. In the sensor based arrangement use quickening agent and whirlygig to identify irregular driving conduct, while joins sensors by utilizing Inertial Measurement Units on smart phones. To conquer the disadvantages of this system, we further propose a fine-grained unusual Driving conduct Discovery and recognizable proof system, D3, to perform ongoing high-precise anomalous driving practices observing utilizing smartphone sensors. We utilize the acoustic signs for early acknowledgment of this distracted driving conduct.

III. PROPOSED MODELLING

The drivers encounter a variety of road hazards because of their unawareness of being in inattentive driving state, for example, eating or picking up things while driving. Our goal is to build a system for early recognition of these driving events by utilizing existing smart phone sensors. These Distracted driving occasions are potentially presenting drivers in danger.



From earlier studies conducted, there are four kinds of the most generally happening distracted driving occasions of drivers themselves. The early recognition (ER) is based on machine learning recognition of these driving events, which has drastically improved the accuracy of prediction of such driving events. Distracted driving occasions can be perceived before a particular occasion is half-way done by distinguish driving behaviors utilizing sensors installed in smartphones, for example, accelerator, gyroscope, and camera. There have been existing investigations on recognizing abnormal driving behaviors including distracted, drowsy and drunk driving. These investigations distinguish driver's status based on pre deployed infrastructure, for example, cameras, infrared sensors, Existing system quantitatively evaluate driving styles by normalizing driving behavior based on personalized driver demonstrating. Some existing works realize driving occasion's identification by utilizing professional infrastructure including EEG and water cluster detectors, or basic sensors, for example, infrared sensors and cameras. Notwithstanding, the arrangements all depend on deployed infrastructure and additional hardware that incur installation

IV. METHODOLOGY

Distracted driving comprises of four types of driving events: Fetching Forward, Eating or Drinking, Turning Back, Picking Drops. Our objective is to recognize these distracted behavior elements and alert the driver before any of these events lead to a potential accident. We use Doppler's shift on audio signal to detect distracted driving. Doppler's effect is the change in frequency of the waves of observer, related to the source.

Doppler's effect mathematically expressed as the following:

$\Delta f = 2vcos(\theta) / c \times f_0$
 Where c and f_0 denotes the speed and frequency of the signal. First, the audio signals are collected using an Android application then, we convert those audio signals to Doppler frequency-time profiles, using Fast Fourier transform. While selecting the monitoring frequency of the audio signals, we consider two main factors: background noise and unobtrusiveness. Studies suggest that frequencies in the range of 50 Hz to 15 kHz encompasses most of the sounds which occur in nature and is under the range of human hearing, so we use a frequency which is more than 15 kHz. Using the above equation, we come to know that, more the frequency will lead to more accurate frequency-time profiles. Considering everything, we select the frequency f_0 as 20 kHz. This filtered out frequency samples processed using Fast Fourier. Fast Fourier transform mathematically expressed as let x_0, x_{N-1} be complex numbers, then:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} = \sum_{n=0}^{N-1} x_n w^{-kn} \quad k = 0, \dots, N-1$$

Where $w = e^{i2\pi/n}$ is the first complex N-th root of 1.

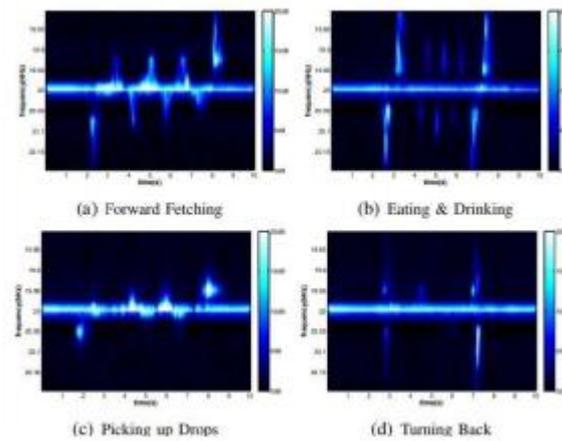


Figure 1: Frequency of Doppler Effect in inactive driving

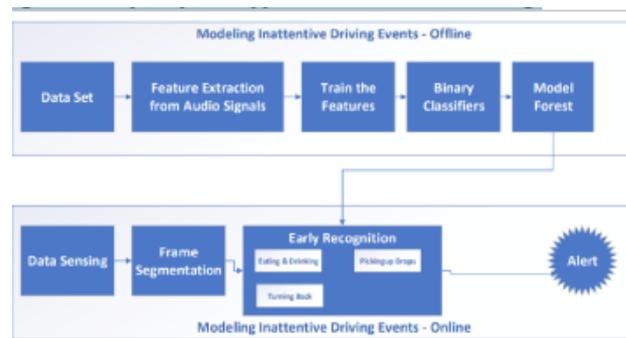


Figure 3: Block diagram

Dataset Uploading: The dataset collected via an Android Application, which specifically developed for this purpose. This data processed to frequency-time profile, using Fast Fourier transform.

Creating Binary Classifiers: Binary classifiers used to classify one event from another. To design a binary classifier, we need to extract the distinguishable features from the data. To extract these features, we use an analysis technique known as Performance Component Analysis (PCA). Which uses a matrix W to store the data according to the variance, which is calculated using Single Value Decomposition Matrix, which is given by: $X = U \Sigma W^T$ Form \times n matrix X , U is a $m \times m$ unitary matrix, Σ is a $m \times n$ matrix with a non-negative singular values on the diagonal. W is a $n \times n$ unitary matrix. Having n orthogonal values ranked by importance. To identify the minimal variance entry, we use the following object function:

$$\min_d \left(\sum_{i=1}^d \sigma_i \right) / \left(\sum_{i=1}^n \sigma_i \right) \geq t \quad t \in [0, 1],$$

Where σ_i is the i th largest singular value of matrix X , which denotes the importance of the i th features, and t is the threshold of reconstruction, denoting the remaining information of the raw data. In ER, t is set to be 0.97 to guarantee the feature's validity. For all four Distracted driving events, we have $d = 19$ from using the above equation, which is a bit larger value. To reduce the value of d , we analyzed the dataset in pairs, which showed that $d=2$, is good enough to represent most of the information in raw data.



From this we can infer, that to achieve pinpoint accuracy in detecting these driving behaviors, we need to use binary classifiers. We now train the binary classifiers using the dataset we have obtained, to distinguish these Distracted driving behavior separately. We, then use a voting mechanism to form a multi classifier, which will classify these distracted driving behaviors. The voting mechanism works in the following way. To differentiate 'a' an event and 'b' an specific event.If the classifier identifies the event as event b, then event b gets the vote as $v_b=1$, whereas event a gets the vote $v_a=0$, since the event was classified as event b. Similarly, a set E having m events will have $C_m \geq 2$ events. All the votes of the binary classifier in that set identified as:

$$V(e) = \sum_{j \in [1, C_m]} v_j,$$

Where v_j is a vote vector of k elements that denotes the vote of the j th binary classifier. The maximum vote for c for j th binary classifier is given by:

$$c = \max_j V_j(e) \quad j \in [1, k],$$

Where c denotes the classified event of e. For some types of events, there are exactly k-1 classifiers, so the condition matched to be the classified event of that particular event.

Frame Segmentation: To recognize the current driving elements, we need to set the time duration for which we will be sampling the audio signals, by setting the start and end. We can accomplish this by monitoring the shifts in the Doppler time-frequency plots. With an exhaustive report, we could observe that, as the occasion keeps on occurring, the average sufficiency keeps a generally higher value, when an occasion occurs than an area with no occasion event. In view of the average plenty-fullness pattern in Doppler shift pattern, we can utilize sliding window to set the span. In sliding window, ER continues assessing the Doppler shift adequacy pattern, in a window and figures the edge an incentive to determine start and end of the driving occasions. After choosing the startpoint in distracted driving, the ER portions the information into frames and finishes the current to beginning frames for early acknowledgment.

Recognition and Alert: When distracted driving perceived, ER separates features from portions and identifies whether the occasions are distracted driving occasions or other driving behaviors at some beginning periods depending on the prepared model forest. If any of the four distracted driving occasions perceived through the above methodology, ER sends a notice message to alert driver. The message sent on the mobile app, which was prepared for collection of inputs, in the form of audio signals and in the form of notification, once the user has downloaded the mobile app from the play store. Specifically, to get a steady F-score, ER needs 250 training tests for Fetching Forward, 346 examples for Eating or Drinking, 358 examples for Turning Back and 478 examples for Picking Drops. We use as much training datasets as we can to get the opportunity to ensure the performance of ER. Hence may affect the performance of ER. Also, during peak time, the F-scores of Early Recognition is lower than the F-scores during off-peak time since overwhelming traffic condition may bring more stops

for vehicle and more driving behaviors, for example, shifting gears, which may result in more mistaken recognitions. From our experiments and studies, we have come to know that our accuracy of prediction is dependent on the placement of the smartphones. For example, smartphone placed in the instrument panel (left and middle-part), near car doors and cup holders as well as in driver's pocket expected to deliver good F-scores. F-score for any smartphone placement and any inattentive driving event is above 90%, which is acceptable for using ER in real driving scenario.

V. RESULT AND FUTURE WORK

This project can be improvised by adding components that can be able to predict the inattentive driving of many cases, By arranging a camera which had been already in smartphone we can be constantly recording the rivers activities, This may be also helpful for tracing the data of accidents. We have been using different sensors present to detect the inactive driving and this can be considered as our future work, If this will be implemented it may reduce many accidents.

VI. CONCLUSION

In this paper, we have addressed the problems of inattentive driving and had been recognizing it as early as possible for the safety. We have proposed a system that will be recognizing the inattentive drive before and alerting. It will be recognizing different in attentive driving like fetching forward, eating and drinking, turning back, picking up drops etc., this will be intimated using a smartphone which is already installed in cabs, this will be containing a data that will be refreshed after every ride. We will be training the model by using the real life-driving environment so that it can recognize and prevent the accident. This will be having a High accuracy rate of recognizing and realizing the inattentive driving in early stages.

VII. REFERENCES

1. US Legal, "Inattentive driving law and legal definition." [Online]. Available: [http:// definitions.uslegal.com/i/inattentive-driving](http://definitions.uslegal.com/i/inattentive-driving), 2016.
2. U. D. of Transportation, "Traffic safety facts research note, distracted driving 2014." [Online]. Available: [https:// crashstats.nhtsa.dot.gov/Api/Public/View Publication/812260](https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812260), 2016.
3. U. D. of Transportation, "Faces of distracted driving." [Online]. Available: [http:// www.distraction.gov/faces/](http://www.distraction.gov/faces/), 2016.
4. [4] C. C. Liu, S. G. Hosking, and M. G. Lenne, "Predicting driver drowsiness using vehicle measures: Recent insights and future challenges," Journal of safety research, vol. 40, no. 4, pp. 239-245, 2009.

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