

D&RSense : Detection of Driving Patterns and Road Anomalies

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Abstract— Driving style analysis and road anomaly detection have a remarkable impact on road safety. They directly influence road accidents and have been a vital area of research in order to address road safety problems. In this paper, a system called D&RSense have been proposed that uses GPS and accelerometer of smartphones to categorize driving style of drivers, assess the road quality as well as to give real-time warnings to drivers in order to make driving safer. D&RSense does the categorization through detection of driving events like acceleration and braking and road anomalies like bumps and potholes by using the popular machine learning technique, Support Vector Machine (SVM) and gives real-time warning and instructions to drivers using a locally running Fast Dynamic Time Warping (FastDTW) algorithm. Extensive experiments have been conducted to evaluate the effectiveness of the proposed system.

Keywords— Driving style analysis; Road quality detection; FastDTW; SVM

I. INTRODUCTION

A safe and efficient transportation system is one of the key requirements of a smart city. World Health Organization showed that nearly 1.25 million people die in road traffic accidents every year [1]. In fact, a research by the American Automobile Association showed that unsafe driving accounted for more than 56% of road accident fatalities [2]. Also, poor road conditions with bad lighting may lead to accidents. Now, mainly due to infrastructural and economic challenges, countries may struggle and lag behind to address these transportation safety concerns. As a result, drivers become careless and neglect existing law enforcements. Investing in loop detectors or constant vigilance through CCTVs throughout a city can be pretty expensive. So, a cost-effective and real-time solution for road safety monitoring was very much in need.

Modern smartphones, which have become extremely popular among people, come with a variety of in-built sensors like accelerometer, GPS, magnetometer, gyroscope, proximity sensors etc. Utilizing the data gathered from these sensors in order to detect aggressive driving events incur almost no cost at all. One can resourcefully monitor the driving pattern as well as detect road condition using the information gathered from his or her smartphone.

In this paper, we have proposed an economical and highly efficient sensing approach named *D&RSense* comprising of the smartphones of commuters who contribute their cruise data in this participatory sensing approach in order to make

driving safer and more comfortable. The proposed system functions in a two-fold way:

- a) *D&RSense* detects aggressive driving events efficiently and in real-time, utilizing the GPS and accelerometer sensors present in Android based smartphones and then by applying FastDTW on it. It immediately warns the driver in to avoid accidents. The entire processing is done in the smartphone itself.
- b) *D&RSense* also utilizes the entire data recorded from different complete trips for more refined and accurate analysis using SVM in a cloud infrastructure to maintain complete driver profiles and detect damaged road segments across the city.

Also, even if a driver who is aware of his aggressive tendencies, chooses not to use the application, one can still use the passengers' phones to monitor his driving. Most importantly, the simplicity of the application, its beneficial results along with the portability and widespread availability of smartphones will encourage the people across the city to participate in this attempt to build a safer city.

The detailed objectives of D&RSense so far are to:

- i. Identify aggressive driving events like sudden acceleration, braking and road anomalies like bumps and potholes from the real travel trajectory information of a driver along with the information gathered from his smartphone's accelerometer.
- ii. Give real-time driving warnings to a driver when he or she drives aggressively.
- iii. Categorize the driver into as of aggressive or calm nature through scoring.
- iv. Identify road segments across the city covered with bumps or potholes.

Now bikes are seen to be at the highest risk when it comes to road accidents among the common modes of transportation. The U.S. government's data from 2014 show that for every mile traveled, that year, the number of motorcycle-related deaths was 27 times the number of car-related deaths [3]. So our initial experiments have been concentrated solely on bike transportation data.

The organization of the paper is as follows. The related works are discussed in Section 2 followed by our problem statement along with the preliminaries in Section 3. The system architecture, implementation and workflow have been explained in detail under Proposed Approach in Section 4. The experiments and results are then discussed under Evaluation in Section 5. Finally, the paper concludes in Section 6.

II. RELATED WORKS

Event detection using smartphone sensors to build an intelligent transportation system has been a very popular area of interest in the recent years. In the paper by Chandrasiri, Nawa and Ishii, the authors have demonstrated the assessment of driving skills utilizing the data obtained from a driving simulator and then by using machine learning algorithms, k-NN and SVM on it [4]. Johnson and Trivedi, in their paper, have proposed an application called MIROAD, which used classical Dynamic Time Warping (DTW) algorithm to utilize the data gathered from smartphone sensors to detect driving events and showed that the app successfully detected aggressive driving events [5]. In the paper by Dai, Teng, Bai, Shen and Xuan, the proposed program running on Android G1 phones detects drunken driving maneuvers utilizing the data sensed from the accelerometer and orientation sensors [6]. DUII (Driving under the Influence of Intoxicants) has been a major cause of road accidents and the paper shows that the program works well with very low percentage of false positive and false negatives. Then, Saiprasert, Pholprasit and Thajchayapong, in their paper showed detection of driving events using data collected from smartphone sensors such as GPS receiver and accelerometer sensor conveniently without the aid of external sensors or hardware [7].

The above mentioned papers, though motivating, have some limitations which D&RSense has tried to overcome. D&RSense is a simple and efficient application that runs successfully on Android based smartphones and has been built keeping time as well as accuracy in mind.

The novel contributions of this paper are:

- All experiments have been conducted on real data gathered from smartphones' GPS and accelerometer sensors while riding bikes.
- For driving event and road condition detection, a comparison of the methods, FastDTW and SVM has been performed before drawing inferences.
- D&RSense can also successfully detect the locations where drivers tend to drive aggressively or where the road condition is poor.

III. PROBLEM STATEMENT AND PRELIMINARIES

A. Problem Statement

Let $trip_data$ be a set of time ordered observations $\{t_1, t_2, t_3 \dots t_m\}$ such that each $t_i = \{lat, long, ts, acc_x, acc_y, acc_z\}_i$ where, $lat, long, ts, acc_x, acc_y, acc_z$ represent the latitude, longitude, magnitude of acceleration along x, y, z-axis of the tri-axial accelerometer of a smartphone during the i^{th} observation respectively.

Let an event e be a subset of $trip_data$ which identifies any one of the particular phenomenon, namely, *sudden_brake*, *sudden_acceleration*, *bumper*, *pothole* and *normal_data*.

Now, from a given $trip_data$ for a driver, one identify an event set $E = \{e_1, e_2 \dots e_n\}$ and accordingly classify the driver into type T_d and a road segment as T_r where,

$$T_d = \{aggressive, calm\}$$

$$T_r = \{bumpy, pothole_filled, normal_road\}$$

B. Preliminaries

Nowadays, almost all smartphones are equipped with a tri-axial accelerometer that can measure acceleration in 3-D along the x, y, and z axes. By looking at the pattern of acceleration generated in a phone while travelling on a bike particular things can be inferred as shown in Fig. 1.

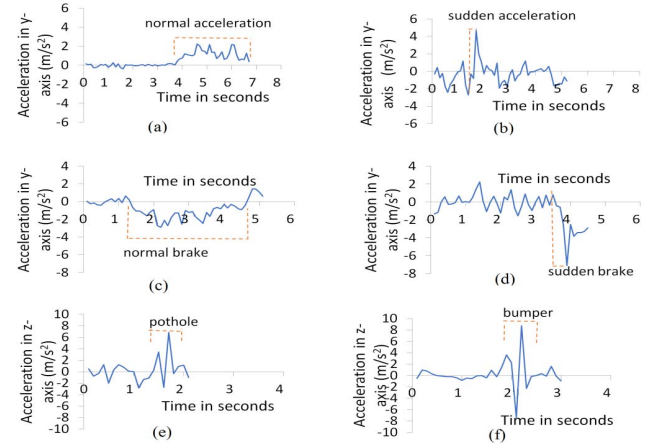


Fig. 1. Driving events captured from smartphone sensor's raw data (a) normal acceleration (b) sudden acceleration (c) normal brake (d) sudden brake (e) potholes (f) bump

A sudden acceleration would cause a sudden surge along y-axis (depicting magnitude of the acceleration) whereas in a safe acceleration the spikes would be gentler as shown in Fig. 1(b) and 1(a) respectively. Similarly, braking events could result in dips along y-axis as shown in Fig. 1(c) and 1(d). Both a bump and a pothole would cause spikes and dips along z-axis as shown in Fig. 1(e) and 1(f) respectively and by considering this one can infer if the road is bumpy in nature.

However, it has been observed during the experiment that a combined effect of accelerations along the three axes gives better results in predicting the driving event instead of considering separate accelerations along the three axes. Moreover different drivers across the city will have different patterns of generating aggressive events. Our motive is to train our model so that it would be able to identify the patterns in order to detect driving and road anomaly events at different speeds and under various circumstances.

IV. PROPOSED APPROACH

A. Architecture

The architecture of D&RSense is depicted in Fig. 2, which consists of three layers, namely *Crowd layer*, *Local Processing layer* and the *Cloud layer*.

Crowd Layer

The bottom most layer is the Crowd layer. It consists of the smartphones of drivers and passengers in the city that have our D&RSense application installed and running. It collects data

through the smartphones' GPS and accelerometer and passes it to the Local Processing layer for further processing.

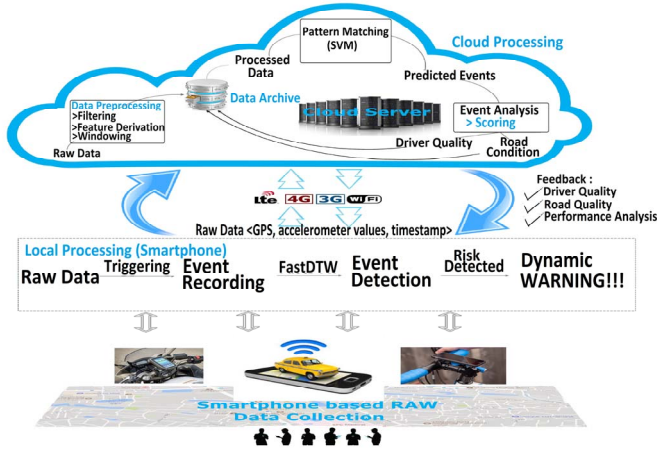


Fig.2. Architecture of D&RSense

Local Processing Layer: In this phase, the model instantly detects aggressive driving events and gives real-time warnings to the driver by using a **Sensor Triggered Fast Dynamic Time Warping (FastDTW) Algorithm**. This detection does not need any active Internet connection and is done locally in the respective smartphones.

The acceleration patterns generated in our smartphones are essentially time series and in order to determine similarity between time series for classifying them properly, a few distance measurement techniques exist for e.g., Euclidean distance, Pearson distance, Spearman distance etc. other than DTW. However, DTW outperforms Pearson and Spearman's coefficient methods [8] and the main disadvantage of Euclidean distance measurement is that even if there be two identical series, but one of them has drifted along the time axis or are of different lengths, they may be considered to be very different from each other [9]. But in this application essentially, the similarity between several time series that differ in length needs to be computed, as for example the time needed to come to halt suddenly by applying brakes will require a much lesser time than to come to halt through normal gentle braking. So, Dynamic Time Warping (DTW) [10] algorithm was considered suitable.

Now, while comparing several time series, forming cost matrices for each pair of time series may become time consuming. The paper by Salvador and Chan shows if FastDTW is used, this classification can be done in $O(N)$ time as the entire cost matrix need not be filled up where as in conventional DTW it needs $O(N^2)$ time[11]. Moreover, if pattern matching is done for every new input data picked up by the accelerometer, it will drain the phone batteries faster. So, in D&RSense, a Sensor Triggered FastDTW is being used i.e. only when the signal will cross certain thresholds, the algorithm will be activated as discussed in the Workflow section below.

Once the trip is over, all the collected data is sent to the Cloud over an active Internet connection for further processing.

Cloud Layer: The volume of data collected from numerous drivers and passengers in the city in this approach over various trips on different days will become too huge to be running on a single phone. To meet the need of extra storage and more accurate processing of the huge data we have the Cloud Layer as shown in Fig. 2. In the cloud, the server has all the raw data files and a classifier where pattern matching for event detection is done to classify driver and road quality.

Here the well-known and powerful classifier Support Vector Machine (SVM) has been used for pattern recognition and event detection as discussed in detail, in the Workflow section. One of the most promising algorithms for driving event detection, SVM [12] outperforms other machine learning algorithms like k-NN [4] and since SVM uses structural risk minimization [13], it does not suffer from local minima. Also, the solution to SVM is global and unique [14]. Moreover, the fact that it has no upper bound on the number of features makes it extremely suitable for this approach. Finally, after comparing the accuracies of linear, polynomial, radial and sigmoid kernels of SVM, the radial kernel has been selected for our approach as it gave the highest accuracy after selecting the proper value of gamma and c. Once classified, the predicted data along with the labels can be added to the training dataset which keeps on growing.

B. Implementation

As already discussed, D&RSense has an Android based application end and a server end. Android Studio 2.3.1 was used as IDE for both design and development of the application. In Android Studio, the user interface elements were generated using XML and Java was used as the programming language. The main functions of the cloud layer are data storage, processing and data analysis. In our work, OPENSIFT have been as our Cloud Service provider. Authentication check for the user was also done here for the driver profile maintenance. So, this layer stores all the driver related data, including authentication and sensed data from the application along with location, time stamp, acceleration patterns, scores and driving nature.

The background processing in the cloud is done in R Programming language. Here, the application's data is sent to the server using the 'POST' method of the HTTP protocol. Each time such an http post request comes from our application, information is extracted from the request message and inserted into the database. In the backend, MySQL has been used as the database and PHP 5.4 as it has a built-in web server which handles requests sequentially and is ideal for quick testing as well as unit testing of web services with the addition of the new session handling class. In the front end, Java Script along with HTML and CSS have been used.

C. Workflow

The workflow of the proposed system D&RSense can be broadly classified into two phases based on their processing plane; viz, Local Phase (in the smartphone) and Server Phase (in the Cloud).

Local Phase

This phase works in a time efficient manner for identification of aggressive driving events in order to generate real-time warnings to the driver. This is achieved by following the mentioned steps below.

1) **Data Collection:** From the instance when the driving mode of the application is activated, by turning “Driving” on (Fig.8), data collection starts i.e., raw time-stamped data from the accelerometer and GPS is recorded in the smartphone itself.

2) **Event Recording:** Whenever the sensors’ signal reading crosses the thresholds as shown in Table 1, local data processing begins. A buffer is maintained where last 10 seconds’ data is stored all the time and if any threshold is crossed the next 10 seconds’ data is appended along with it and this 20 seconds of data is used for local event detection which is enough to capture any driving event for local processing.

3) **Event Detection:** The data collected for local processing is analyzed using FastDTW in order to understand which recorded driving event’s signal data it matches most closely with. It then classifies the events accordingly.

4) **Feedback:** If within a time span of 5 minutes, the event identified by the FastDTW technique is the third or higher consecutive occurrence of any of the sudden acceleration or sudden braking event in number, an instant warning is generated stating the anomaly.

Table 1. ACCELEROMETER THRESHOLDS [7]

Event	Axis	Threshold set
Sudden acceleration	x-axis y-axis	$\geq 0.3 G$ $2.5 G > y > 0G$
Sudden braking	x-axis y-axis	$\geq 0.3 G$ $-2.5 G < y \leq 0G$
Bumper	x-axis z-axis	$\geq 1 G$ $\geq 6 G$
Pothole	x-axis z-axis	$\leq -2G$ $\geq 6 G$

However, the amount of data that can be stored in the smartphone as recorded event patterns will have a fixed upper limit though its contents can be modified periodically using updates from the cloud. Once the trip is over, the “Driving” mode is turned off in the app and all the raw data recorded throughout the trip, is sent to the cloud server over Internet.

Server Phase

This phase utilizes all the raw data gathered during the Local Phase for further analysis with enhanced accuracy and interpretations and does driving style assuming a smooth road as well as road quality analysis assuming a calm driver following the below mentioned steps:

1) **Pre-processing:** Prior to any testing, templates corresponding to each of the driving events like normal and sudden brake, acceleration, potholes, bumps of varying sizes were prepared to train our model. Raw data corresponding to each separate event was collected and feature derivation and feature extraction was performed as discussed below. For testing trip data, a sliding window of size N and step size N/2 is used where N equals to 20 seconds. By sliding the window to N/2, half of the previous window’s data is incorporated in the current window which eliminates the chances of missing

patterns from the filtered data as shown in Fig.4 since real streams of data is being tested.

a) **Derived Features:** The raw data has the features latitude, longitude, timestamp, accelerations along three axes. From these data some more features like variance, standard deviation, maximum of, minimum of, position of maximum and minimum acceleration, zero crossing rate (zcr), mean, median, interquartile range, skew, kurtosis for the acceleration data along each of the three axes has been derived. Along with these, distance, time duration, speed and signal magnitude area for each window has been calculated and a total 40 features has been used for this experiment.

b) **Feature extraction:** Principle Component Analysis (PCA) has been used in order to reduce the dimensionality considering the principle components that has contributed at least up to 97.5% variation in the data. The features chosen through this process are:

i) For driving skill analysis: Time duration, minimum of acc_y , median of acc_y and acc_z , mean of acc_z , variance of acc_y , skewness of acc_x , acc_y and acc_z , zcr of acc_x , acc_y , acc_z , kurtosis of acc_y , position of minimum of acceleration in acc_x , acc_y and acc_z and position of maximum in acc_y were received as primary principal components which caused maximum variation in the dataset and were used to train the model. Here the greater influence of features along the y-axis is due to the fact that the linear component of acceleration in the direction of movement of the bike would have the maximum influence during acceleration and braking, followed by the features of z-axis acceleration since vehicle tend to jerk more as speed increases.

ii) For road quality analysis: The features chosen using the same PCA process were maximum of acc_z , minimum of acc_x , variance of acc_z , kurtosis of acc_x , median of acc_x , acc_y and acc_z , iqr of acc_z , skewness of acc_y . Here, the greater influence of the features of acceleration along z-axis can be explained by the fact and bumps and pothole generates jerking in the car or phone vertically.

2) **Event detection:** We have experimented with the powerful machine learning algorithm SVM for the pattern recognition in order to detect aggressive driving events and road anomaly detection as shown in Fig 4. Here, the signal was generated for an instance where a car applied brakes suddenly because of a bump and then tried to accelerate aggressively. The window successfully detects the sudden brake, bumper as well as the sudden acceleration.

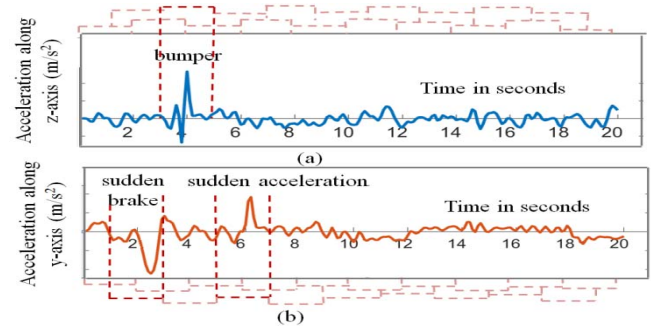


Fig. 4. Event Detection on filtered data shown separately on y and z axes (a) window captures the bumper (b) window captures the sudden braking and sudden acceleration events as well

Once the test data are classified, the data corresponding to the detected events can be added to our training set along with the predicted labels that will make our training dataset ever increasing.

3) **Scoring and Mapping:** Depending on the number of aggressive events in each trip, drivers are scored and by calculating an average score from all the trips of each individual driver, they are categorized to be aggressive or calm as explained. At the beginning of each trip, a driver is given a score of 100 and every time a sudden acceleration is detected, D&RSense deducts 2 whereas for every sudden braking D&RSense deducts 4 points from the trip score as in an urban street, the severity of sudden braking is more than that of sudden acceleration. For every 10km the driver drove without an aggressive event, a score of additional 5 was awarded to him, maximum score being held at 100 and minimum at 0. After each trip, the overall average score is updated and if the total acquired score is found to be greater than 60 the driver is tagged as a calm one otherwise he is tagged to be of aggressive driving nature.

For road quality detection, pothole and bumps are detected from the collected dataset and plotted them in the city map using the GPS information that will be visible to all the users of D&RSense as shown in the result section; when merged in a greater scale this would help to detect the areas of the city where road needs maintenance to build a safer city

V. PROPOSED APPROACH

A. Experiment Setup

The experiment was carried out on bikes using the 4 different Android based smartphones, Redmi 3S Prime (3GB), Redmi Note 4 (2 GB), Asus Zenfone Max (2GB) and Motorola Moto E3 (1GB). The 2 different bikes used in this experiment, one Bajaj Avenger Cruise (220Cc Model) and one Bajaj Vikrant (V15) (150cc Model) were ridden by two different drivers. The dataset was prepared while riding from Jadavpur University Main Campus to Baruipurvia Baruipur Bypass¹ over an approximate distance of 50 km every day from 6th July - 9th August 2017 over a period of 35days. From this data, the event templates were prepared in such a way that the initial training data had an equal number of the specific driving events (normal as well as anomalous). Both types of acceleration templates were prepared while increasing the speed from 0-40, 0-60, 20-40, 20-60 and 40-60 kmph and both the types of the braking templates were prepared while decreasing the speed from as the reverse of all the previous mentioned values. After rigorous data collection phase by the volunteers, we got our initial dataset for the training and testing purpose consisting of 180 observations which have increased to 300+ over the course of the experiment. 4/5th of

the dataset was used to train the model and remaining 1/5th to do the testing.

B. Results

After setting all the conditions as mentioned above, both the ends, local and cloud part of the system were tested for the system's accuracy validation. In order to detect the driving events from given trip information, our locally running FastDTW gave an accuracy of 86.36% whereas SVM gave an accuracy of 95.45%. When the same thing was tested using a threshold based algorithm, it gave a very poor accuracy of 44.34% due to the occurrence of too many false positives.

These classification accuracies are calculated as an average of 20 runs each and each run's accuracy is calculated as:

$$Accuracy = \frac{\text{correctly_detected_events}}{\text{all_events}} \times 100\%$$

Fig. 5 shows that accuracy of both SVM and FastDTW improves as the size of the training dataset increases. FastDTW is getting the dataset updated after every 14 days, whereas SVM's dataset is increasing every day (Fig. 5a) which is reflected in its accuracy as well. Fig 5(b) shows that the threshold based system is almost static in terms of accuracy as is not dependent on the size of the dataset unlike FastDTW and SVM. It can be observed that FastDTW's accuracy is almost steady from day 1 to 14 and from day 15 to 28 of the experiment because the dataset is constant till it gets an update from the cloud. In the same duration, the dataset for SVM is increasing continuously, and so is its accuracy. After the results stabilized, it was inferred that SVM's accuracy for comprehensive data analysis is much higher than that of FastDTW's.

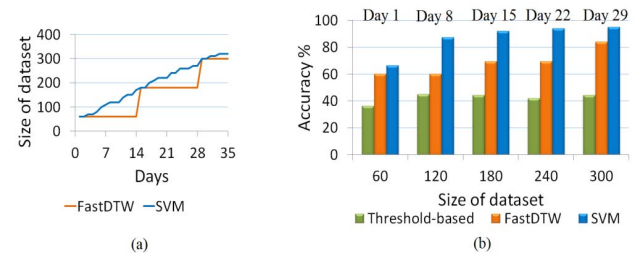


Fig. 5. Accuracy of the techniques improves as the size of training dataset increases

In Fig.6 the correct predictions along with the false positives and false negatives for each event are highlighted, separately for FastDTW and SVM based on the total dataset available for training and testing purposes to understand the system's performance closely. Here, the term event means sudden acceleration, sudden brake, bumper and pothole which affect driving directly leading to accidents and needs to be analyzed separately to evaluate our system's performance.

¹ [EM Bypass, Kolkata, West Bengal, India](#)

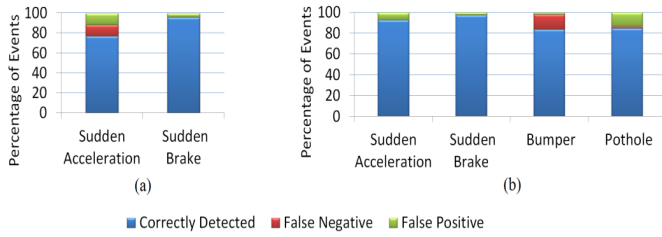


Fig. 6. Event Detection of (a) FastDTW and (b) SVM

Fig. 7 depicts the identified events along the same segment of the test path in the cloud layer using SVM when the same driver on the same bike drove for 2 consecutive days, once calmly and once aggressively. It shows the driving trip trajectories of a driver with the various events detected by D&RSense.

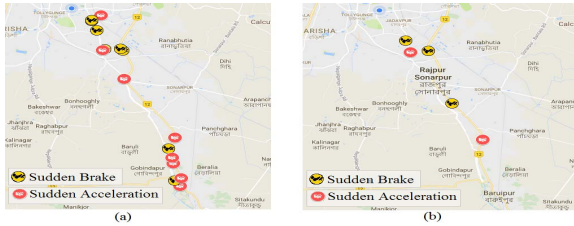


Fig. 7. Driving trip trajectories of a driver while (a) aggressively and (b) calmly

An important part of the application is its various feedbacks based on the analysis in the cloud. Fig. 8(a) shows the basic login screen, whereas Fig. 8(b) shows the data collection page's screenshot when driving is on. Fig. 8(c) is showing an alert generated when more than 3 consecutive rough driving events were detected along with the segment in the map where it was actually detected. Finally, Fig. 8(d) gives the driver the feedback and his overall score which is modified after completion of each trip based on his driving. It is maintained and calculated in cloud and comes back to the user on request.

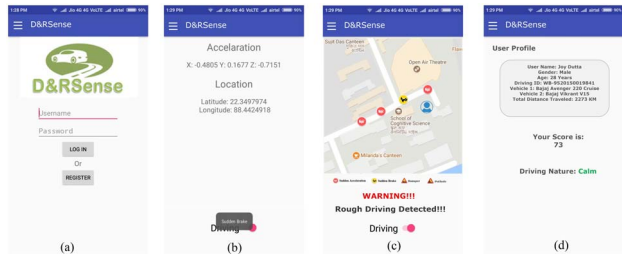


Fig. 8. Screenshot of D&RSense (a) login screen (b) data collection screen when Driving is on (c) warning message on aggressive driving (d) driving score of a driver after completion of a trip

The bumps and potholes correctly detected by D&RSense within two road segments inside the Jadavpur University campus are shown in Fig. 9.



Fig. 9. Detection of (a) bumpers and (b) potholes along road segments in Jadavpur University Campus

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a system called D&RSense that utilizes the smartphones' sensors, to detect aggressive driving patterns from the accelerometer readings of smartphones. FastDTW was used to do local event recognition so that a warning can be issued to the driver in real-time. SVM was also applied while processing in the cloud to do pattern recognition for classifying drivers into aggressive or calm categories and roads into bumpy, filled with potholes or normal categories.

The experiment and data collections are still going on and in a few months the model would perform a lot better than now. As our future work, we would try to categorize the driving style considering the road condition and traffic congestion as well while maintaining different datasets for bike, auto, car and bus data at different times of the day. Currently the scoring system is also at an initial, intuitive stage and has great room for improvement which we will consider during our future course of work. Moreover, the experiments that conducted so far had the phone held horizontally oriented with the bike axes, but we need to consider the fact that the phone can be placed at any position i.e. it can be in our pockets, handbag or on the seat. So, we need to virtually reorient the axes of the phone and then use sensor readings to estimate traffic and road conditions which we will focus into as our next step of work.

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