Amelio-rater: Detection and Classification of Driving Abnormal Behaviours for Automated Ratings and Real-Time Monitoring

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***Abstract*—Real-time monitoring of the drivers may be a factor that would force them to drive safely. In this paper, we introduce a system named 'Amelio-Rater", that focuses on detection and classification of abnormal driving behaviours for automatically generating driver ratings and real-time monitoring. To reduce malicious ratings, the Amelio-rater introduces an automatic rating system which is calculated purely based on the driver's driving behaviours only. Each driver will be given his own Amelio-rater rate and a manual user rate. There are multiple types of driving abnormal behaviours monitored by the proposed system such as meandering, single weaves, sudden changing of lanes and speeding. The classification results achieved showed that the Amelio-rater reached an accuracy of 95% . Our experiments showed that the manual user rates given for the driving behaviour are not far from the rates given by Amelio-rater. Amelio-rater rates were very close to the actual rates given by the users.**

I. Introduction

According to the Association for Safe International Road Travel [13], an annual global road crash statistics stated that up to 1.3 million people die due to road accidents yearly and about 20 million injured. Also according to the WHO [14] over 1.25 million people die and up to 50 million suffer from injuries due to road crashes. This makes road accidents a leading cause of death. Road crashes can not be completely prevented, but certain measures could be taken to try and reduce their occurrence. Most road accidents are caused by human factors such as driving behaviours[15]. Driving abnormal behavior needs immediate attention as drivers will not be always aware of them and may lead to accidents. Abnormal Driving behaviours could be detected using sensors[4] or cameras. Cameras could be used in two ways: to detect the changing of lanes defying the laws of traffic [10] or to detect the driver's condition such as being drunk. Such behaviours could be classified into different types: drivers condition [5][19], road anomalies [3] or the driving activity itself[4]. Most of the recently available rating systems have obstacles when it comes to the reason behind the given rate to the driver by the consumer[21]. Sometimes the consumer would give the driver a high rating value but it is because of his personality, or the other way around. Such ratings may sometimes be biased; however, they should not be ignored completely.

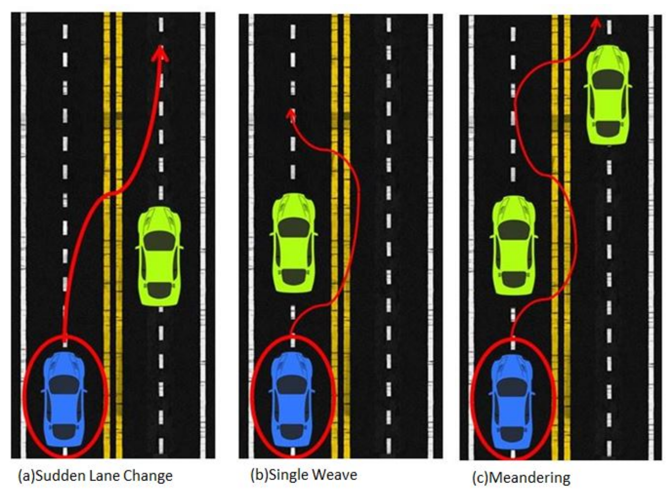

Fig. 1. Illustration of abnormal driving behaviours.

The abnormal driving behaviours that will be focused on are sudden lane change, single weaving and meandering. Sudden lane change is when a car moves from it's current lane to one of the neighbouring lanes in a sudden movement. Single weaving is when a car moves to a neighbouring lane in a sudden movement and then returns to it's previous lane again. Meandering is when a car performs multiple single weaves consecutively. Figure 1 shows an illustration for each of the three abnormal driving behaviours.

The Amelio-rater focuses on driving activity without consideration to road anomalies or drivers condition. The Amelio-rater collects each trips data needed for analysis of the driver's performance. This will be the data used to generate the ratings. The trip will consist of a user driving a car from a source to a destination. The trip's data to be collected will be a series of readings of the following sensors: accelerometer, gyroscope, and GPS with time-stamp. The sensors are built in the smart phones of the drivers. The trip's data is essentially used by the Amelio-rater to classify the driving behaviours being done to be used for the rate generation.

During a trip, every location is stored along with the time-stamp and the behaviour that took place. Using this data, the Amelio-rater will help many transportation business owners when taking crucial decisions against their employees. It will identify if an accident took place due to a reckless mistake done by the driver or not. The automatically generated rate will aid in such decisions as well.

The main problem statement in this research is to ameliorate the accuracy rates of the detection of a driving abnormal behavior in the real time. The main contribution of this work is to automate the ratings and guide the malicious rating data by more trustworthy rates.

II. Related Work

Several systems used different approaches in the areas of detection and classification based on driving patterns. Cheng et al. [22] proposed a system that aims to classify the driver of a vehicle based on the driving behaviour. They used car sensors through OBD-II scanner as well as sensors in the smart phones. When using smart phone sensors only along with Support Vector Machine (SVM) model, they reached an average classification accuracy of 75.83% working offline. Two different data-sets were included in their experiments. One with 14 drivers using 3 different cars, and the other with everyday data collected from people sharing a car.

Aya et al.[1] introduced a technique in where driving events are recognised using sensors on the smart phone. The system detects the driving behaviour and classifies it as normal or abnormal. It detects road anomalies as well(such as road bumps). The two algorithms that were tested were the KNN(K-Nearest Neighbour) and the DTW(Dynamic Time Warping). The detection of whether a pattern is a road anomaly or a driving behaviour was done using KNN. The classification of the detected behaviour was then done using the DTW. The detection reached a total accuracy of 98.67% and the classification reached a total accuracy of 96.75%.

D3 [4] is a system proposed that detects when an abnormal driving behavior takes place, identifies it's type and classifies it. According to D3, there are multiple types of abnormal driving behaviours: weaving, sudden lane changing, sudden braking, speeding, fast u-turns, turning with wide radius. They used sensors in smart phones to detect and identify the six types of abnormal driving behaviors by extracting the sensors' readings. They presented their work by using (SVM) to train driving features and obtain a classifier model. In total, they obtained 4029 samples of abnormal driving behaviors from the collected data by 20 drivers from different communities with different commute routes using 20 smart phones of 5 different types. They have reached an average total accuracy of 95.36% for their system.

Derick A. Johnson et al. [9] uses smart phone based sensor-fusion and DTW using mobile, to detect, recognize and record the driving actions to categorize the driving style as non-aggressive or aggressive. They contribute by fusing related inter-axial data from multiple sensors into a single classifier. They have found among with Jeffrey S Hickman et al. [8] that drivers' behaviors become a lot safer when they are being monitored and have provided feedback.

Rijurekha Sen et al. [17] stated that fleets could be easily tracked with GPS receivers. Such traces, if collected from a wide-range of fleets such as taxi fleets could contribute in delivering significant information to be used in cases such as travel patterns and road anomalies.The main fleeting system they have focused on is the taxi. They observed a mismatch in demand versus supply for this taxi fleet at certain locations and periods of the day. This could make the passengers feel anger from not having the appropriate taxi driver in some locations.

Kristina et al. [18] created a tutorial to evaluate drivers via a motion-based driving simulation. They collected data on the performance of the drivers' behaviours and produced an overview method for analysing such data. Their main aim was to automatically analyse driving behaviour using simulation software. They have also focused on recording the psychological and physiological reactions of the drivers during the evaluation.

Andreas Riener et al. [12] stated that gathering information about roads from users is helpful for safer and more efficient driving. They introduced a "Social Driving app" where they have created a ranking system to stimulate the drivers to follow system instructions. They provide drivers with information about how to drive ideally in routes that they are not familiar with.

In the Amelio-rater, the behaviours that were trained and tested overall are meandering, sudden lane changing, single weaves, and speeding. Like some of the systems mentioned above, the Amelio-rater will work on classifying the behaviours done by the driver and it will introduce a method to generate an automated rating for the driver based on his/her classified behaviours.

Since we have a focus on the classification of the driving behaviours, we will be testing the Amelio-rater using a hardware setting consisting of a smart phone with the applicable sensors(GPS, accelerometer, and gyroscope). The Amelio-rater works online where the behaviours are classified in the real time, and the user is instantly notified if an abnormal behaviour was done. The classifiers that will be used in the evaluation are going to be the DTW and the SVM. We introduce a method which could be more generalized to be scalable enough to be used in multiple fleeting systems such as transportation companies, public transportation(buses), school/private institutions transportation..etc. The Amelio-rater is different from [9] and [4], in means of rating the driver during trip online. The classification is done in the Amelio-rater prior to generating the automated rating. The data stored from the classification process for each trip performed by a driver is used by the rating module for generating the appropriate reports. The entire process takes place in the real time, where the behaviours are classified during the trip and the rate is calculated and stored once the trip is completed.Table I shows the key differences between the related work that classifies abnormal behaviours, and the Amelio-rater.

Related Work	Algorithm	Online	Rating	Accuracy
Driver classification based on driving behaviors[22]	SVM	No	No	75.83%
Recognizing Driving Behavior and Road Anomaly using Smartphone Sensors[1]	DTW, KNN	No	No	96.75%, 98.67%
D3: Abnormal driving behaviors detection and identification using smartphone sensor[4]	SVM	Yes	No	95.36%
Driving style recognition using a smartphone as a sensor platform[9]	DTW	No	No	97%
Amelio-rater	DTW	Yes	Yes	95%

TABLE I. COMPARISON BETWEEN RELATED WORK AND THE AMELIO-RATER

III. PROPOSED SYSTEM

Our proposed system is a mobile application that uses the mobile sensors-accelerometer, GPS, and gyroscope- to extract driving behaviours' readings. The collected data passes through a pre-processing phase; where noise is cancelled to get better results using low pass filter[4]. The filtered data is then passed to a processing module for classification of the abnormal driving behaviour. Finally, the analysed data takes two paths accordingly,the rating data and classification results are always stored on cloud and a warning message is sent to the driver when exceeding a number of abnormal driving behavior in a specific time limit.

Furthermore, ratings are retrieved from the cloud storage for the business owner and consumers. For the business owner, it is important to know the current location of their employee in order to use the real time monitoring feature. Each location is stored along with the behaviour performed and it's time stamp. Such information could be very useful to generate reports about street conditions, if for example a specific behaviour is repeatedly detected at the same location. Figure 3 shows the details of our system. The system overview is divided into three main blocks. The first block is responsible for the data collection and pre-processing where the data to be analysed is collected using the smart-phone. The second block is responsible for the processing of the data, this is where the classification takes place. The third block is responsible for sending the feedback from the analysed data to the users. The data is stored on a cloud storage (Mongo db).

A. Pre-processing

The readings collected from the smart-phone for each behaviour consisted of the accelerometer sensor readings (ax, ay, az) and the gyroscope senor readings (gx, gy, gz) related to that behaviour only. Also the readings for the current location (latitude, longitude) are collected via the GPS. The accelerometer sensor readings will be used independently for the speeding detection as its values are used to calculate the speed. Whereas the gyroscope sensor readings will be used independently for the classification of an abnormal behavior. The gyroscope sensor measures the rate of rotation around a devices x,y, and z axis. The abnormal driving behaviours that are being classified in this paper; except for speeding, depend on change in rotation.

According to[4] we have applied a low pass filter on the accelerometer readings. For the accelerometer sensor readings, the gravity value is removed to prevent it from causing any noise.

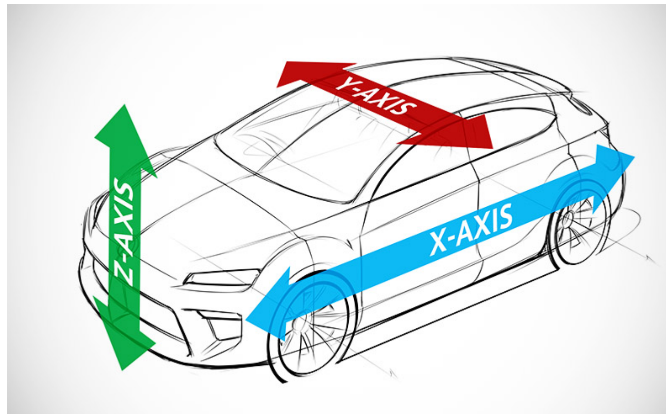

Fig. 2. Illustration of the car and the x,y,z co-ordinates.

In the real-time, the readings are in a stream. The stream of reading needs to be cut into portions to be classified. Those portions of readings pass through a window that accepts a certain number of points(sensor readings). In order to select the appropriate window size, we have done an empirical study with (100,125,150,200,250,275,300) points. As a result of our study we have selected a window size of 250 with overlapping 25% of old window. Each 250 points are passed through the classifier to classify which behaviour is currently taking place.

Figure 2 shows the co-ordinates of the car. These co-ordinates will be the same as the smart phone used.

B. Processing

After the data has been passed through the pre-processing, processing off-loading takes place. The processing done is classification of the behaviours using the DTW classifier.

DTW is used to compare the time-series of the gyroscope's readings against the training data sets [16]. It gets the Euclidean and Manhattan distances between them which is the sum of squared distances of each nth point in one time series to the nth point in the other time series. It later chooses the best fit behaviour according to the training data set and the threshold set based on analysis obtained from averages of samples of each training data set. In order for the DTW to find similarities between two time series, the lengths of the time series may vary[7]. This occurs when the time series are slightly or very much out of phase.

We have two time series in our implementation. The first time series consists of 250 normalised points from the training

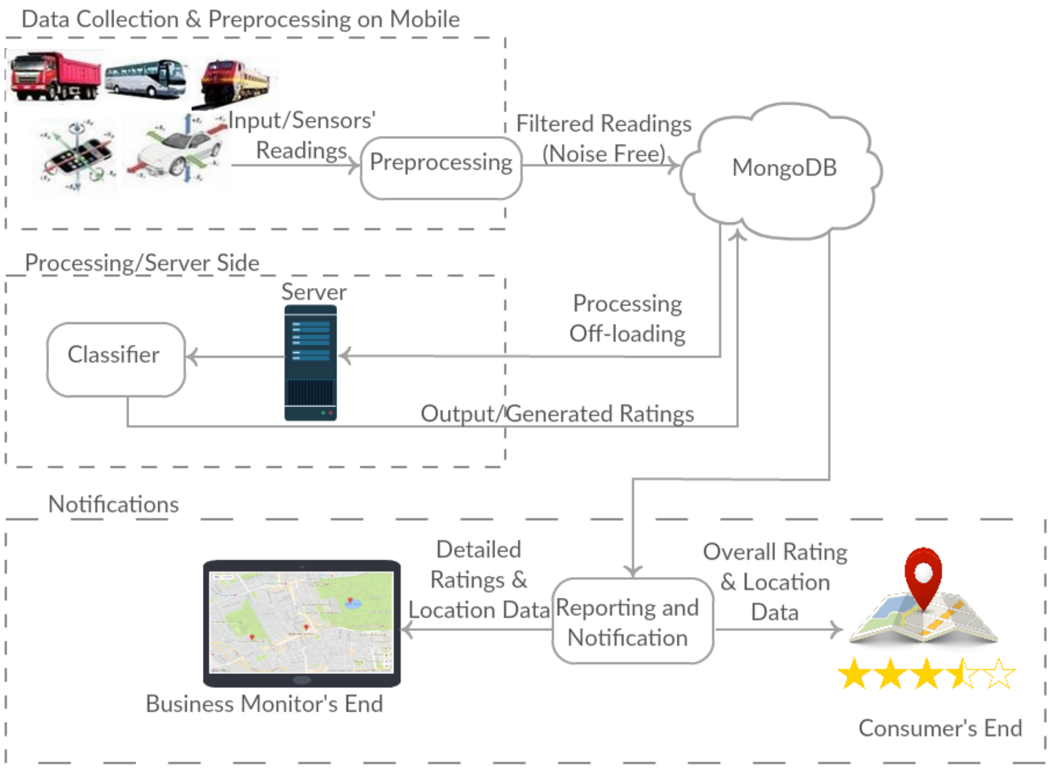

Fig. 3. Amelio-rater system Overview

data set. The second time series consists of 250 points from the testing data set. Each point in both time series includes the x, y, and z values for the sensor's reading. Both time series are compared against each other, by comparing each point from the testing time series one with it's corresponding point from the training time series. Euclidean distance is used to calculate the distance between each two points:

$$dist_i = \sqrt{|gx_2 - gx_1|^2 + |gy_2 - gy_1|^2 + |gz_2 - gz_1|^2} \quad (1)$$

The sum of all the 250 distances between each two points ($dist_i$) in the time series is calculated. We have training data sets for each individual behaviour. The same process is done with the same time series for the testing data set, against a time series of the other training data sets left. The sum of distances is called the cost. The minimum cost between the testing data set and all the training data sets is computed to classify the behaviour.

SVM is a classifier that is a machine learning method that uses statistical learning; it is applied on different data that have bi-classes or multi-classes[6]. It does not suffer limitations of limited samples [2] [20]. Performance of SVM is very sensitive to how the cost parameter and kernel parameters are set. Mapping the data into a higher dimension is known as kernelling. The kernel used is Linear Kernel. To create the SVM model, alternating between 1 - 3 training data sets for each behaviour was done until best results were reached having 3 training samples for each behaviour in the model. Similar to the DTW, two time series were used: testing and training, in order to train the model. The time series used were readings measured by the gyroscope sensor. When experimenting, the same training and testing time series were used with the SVM and the DTW.

C. Learning New Behaviours

The Amelio-rater is trained for 3 abnormal driving behaviours only. However, there are numerous abnormal driving behaviours that could be done by drivers. To avoid having an unknown abnormal behaviour to be classified as a normal a threshold is set. The threshold was deduced based on observing the distances generated when performing a behaviour that is not considered normal, yet the classifier is not trained to classify it. In case of the distance being within the acceptable limits the abnormal driving behaviour is flagged as safe otherwise, it is flagged as unsafe and becomes potential new abnormal driving behaviour that can be trained later on. That way, no untrained abnormal behaviour is counted as Normal, and it will be considered in the rating as an abnormal behaviour; thus maintaining the rating system without it being biased.

D. Rating

There are three different rates used in the Amelio-rater. The first type is the current user rate is the rate given to the participant driving in this experiment by the user riding the car with him/her. The second type is the total driver rate is the averaged rate of the participant, after accumulating all the ratings entered for him/her by users riding with him/her. The third type is the Amelio-rater rate is the rate automatically generated rate by the Amelio-rater.

The driver's rating is calculated as an equation which is dynamically stored in the database. The rate is an average of all the trips performed by the participant. The number of occurrence of each behaviour is kept track of. Each driver in the Amelio-rater is given a label and a numerical rate value. To obtain the label for the drivers, the probability p of an abnormal behaviour is calculated:

$$p = \frac{\sum_{i=0}^{m} event(i)}{\sum events} \tag{2}$$

where m is the number of abnormal driving behaviours found in the Amelio-rater, and $event(i)$ is the total number of occurrences of each abnormal behaviour in a trip. Sum of all abnormal behaviours done is divided by the sum of all $events$ done in a trip; whether it is an abnormal or normal behaviour.

Using the value of p from the equation above, the driver is given a label according to the cases below:

$$f(p) = \begin{cases} Cautious & 0.0 \leq p < 0.1 \\ Novice & 0.1 \leq p < 0.3 \\ Intermediate & 0.3 \leq p < 0.5 \\ Reckless & p \geq 0.5 \end{cases} \tag{3}$$

There is a maximum numerical value a driver can hold as a rate. The numerical rating in the Amelio-rater is calculated by deducing a percentage out of the maximum rate using the probability p calculated earlier.

E. User Interface

Real time monitoring and observing of abnormal driving behavior is the bedrock to enhance driving evaluation systems [11]. The rating systems of the drivers should mainly aim to provide consumers with trustworthy feedback; which also assists the business owner gain high accuracy overview of the performance quality of the hired professional drivers.

The Amelio-rater's mobile application mainly handles the collection of data and the pre-processing. The driver will be able to preview his/her rating for each individual trip performed, and the overall automatically generated rate by the Amelio-rater.

The business owner will be able to track each driver during their working hours. The business owner will be given access to a web interface where s/he can preview a car on a map indicating each driver performing a trip as shown in Figure 4. The car will indicate both the location and the behaviour being done by the driver. The location is indicated by the car's position on the map, and the behaviour by the car's colour. The car's colour changes according to each behaviour, and a legend is provided on the web page.

If the business using the Amelio-rater is a private taxi company, another stakeholder will be considered known as the consumer. The consumer is the user who is in need for a trip to be performed by the driver. The consumer will be given access to preview the driver's rates (manual rates given to the driver by other users, and automatic rate given to the driver by the Amelio-rater).

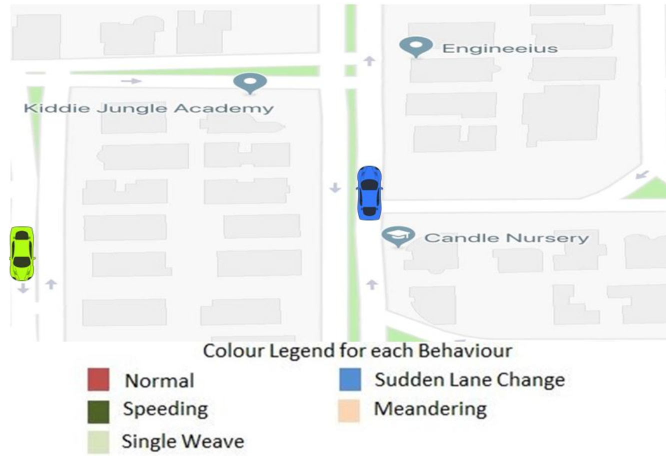

Fig. 4. Sample image of the map user interface and the colour legend.

IV. Experiments

The Amelio-rater is evaluated via two experiments that were designed to test the classifier and determine its accuracy to evaluate the Amelio-rater.

The first experiment was done to choose the classifier to be used for evaluating the Amelio-rater. The classifiers tested were the SVM and DTW.

The second experiment was done to determine the accuracy of the DTW when working online and classifying behaviours in a stream of sensor readings from a trip being performed in the real time. It also had an objective of evaluating the Amelio-rater in real time while considering user's feedback for the automatically generated rating.

A. Data set

The training data set used was collected by 2 drivers using a manual sedan car before starting with any experiment. The sensors data were collected using a smart phone with gyroscope and accelerometer sensors built-in. The behaviours that were recorded are meandering, single weaves, and sudden lane changes. A single behaviour is recorded at a time; and the time taken per behaviour recording is less than a minute, and the street is a local street located with speed limit of 60 Km/s. We have recorded for each behaviour 11 trials, then we applied cross-validation [7] to select the best three behaviours as training data set. The mobile device is placed inside the car being driven to perform the behaviours on a flat surface in a horizontal position pointing towards the front.

V. Experiment 1: Offline Classifier Selection

To try to enhance the Amelio-rater, we decided to test it with two different classifiers. Two classifiers were subject for testing accuracy, DTW and SVM. In this experiment, we have used a sedan manual car. The experiment is guided by us (authors of the paper), where we ask the driver to choose one of the abnormal behaviours in sequence. The driver has to repeat each of the 3 behaviours 5 times. Each time the driver performs an abnormal behaviour, the sensor readings are stored in order to be classified later. We had run the experiment over the offline collected data to acquire the results.

A. Experiment 1 - Results

Results were calculated for each behaviour using both classifiers. Using the DTW we achieved an accuracy of 75% for meandering, 62.5% for sudden lane change, and 100% for single weaving. Using SVM we achieved accuracy of 37.5% for meandering, 50% for sudden lane change, and 62.5% for single weaving. This resulting in an overall accuracy of 79.17% for DTW and 50% for SVM. It could be seen from the results that the behaviour that is least accurately classified is the sudden lane change. The accuracy mentioned show a noticeable difference between the SVM and DTW; where the DTW showed better results in the classification of all three behaviours. Thus, DTW will be used in the evaluation of the Amelio-rater.

B. Experiment 2 - Online Classification Study and User Study for Rating Experience

The main goal in this experiment is to check the accuracy of the DTW classifier when classifying multiple behaviours in a stream of readings in the real-time. It also aims to get the user feedback for the automatically generated rate by the Amelio-rater. Sedan manual and automatic cars were used. The device being used must be connected to an internet connection and GPS must be enabled. Trips performed ranged from 15-20 minutes in three different local streets with maximum speed of 90 km/h.

The experiment was done by 13 participants. The driver (test candidate) was asked to perform a normal trip by the car. In this trip the driver should perform an average of 20 abnormal behaviours, in different time intervals guided by us.

The trips to which the rates are being generated are the same trips in Experiment 1. A manual rate by the user(passenger) was given for the trip performed, and an automatically generated rate by the Amelio-rater as well.

We asked the drivers to exceed the specified speed limit and perform an abnormal driving behaviour at the same time, in different time intervals as well.

After the trip is done, a manual rate by the user(passenger) was given for the trip performed, and an automatically generated rate by the Amelio-rater as well.

The speeding is detected using the GPS sensor built in the smart phone where the speed is calculated using change in position and time. When the driver is exceeding the specified speed limit, the mobile device will give out a beep to notify him/her. Speed limits of different streets are stored in the database, to be easily accessed by the Amelio-rater to compare the current speed value against the street's speed limit. As the driver is doing an abnormal behaviour, the Amelio-rater is supposed to notify the driver. For instance if the driver did a sudden lane change, s/he will hear a voice over from the mobile device saying "Sudden Lane Change"; same for the other two behaviours. The participants were asked to keep track of the abnormal behaviours classification feedback in order to report about Amelio-rater. The participants were accompanied by one of the authors to assist in the evaluation process.

At the same time, if the business monitor has the real time monitoring page opened, a car appears on the map for each trip being performed at that time; changing it's colour when an abnormal behaviour occurs.

Accuracy in the Amelio-rater is determined by calculating the ratio of True Positives(TP) and False Negatives(FN).

True Positives(TP) are the correctly predicted positive values (Abnormal Behaviour) while actual value is Abnormal Behviour.

False Negatives(FN) are the incorrectly predicted negative values (Normal Behaviour) while actual value is Abnormal Behaviour.

Confusions between different types of abnormal driving behaviours were calculated using the format shown in table II.

Final Accuracy of correctly classifying abnormal driving behaviours were calculated using table II as a percentage of the following:

$$Recall = TP/(TP + FN)$$

where $Recall$ is the ratio of correctly predicted positive values(Abnormal Behaviour Type) to all predicted values in the actual class. For example if the actual class is Meandering, the ratio calculated is the number of meanders correctly classified to the number of meanders incorrectly classified as either Sudden Lane Change or Single Weaving.

1) Experiment 2 - Results: At the end of each trip we have asked the drivers for the misclassified movements done by our system. According to the drivers' feedback under normal conditions, all drivers stated that 9 out of 10 behaviours (false positive) done are correctly classified. It was also stated that when the driver is performing a behaviour that is not considered in the experiment, it would be classified as one of the three behaviours.

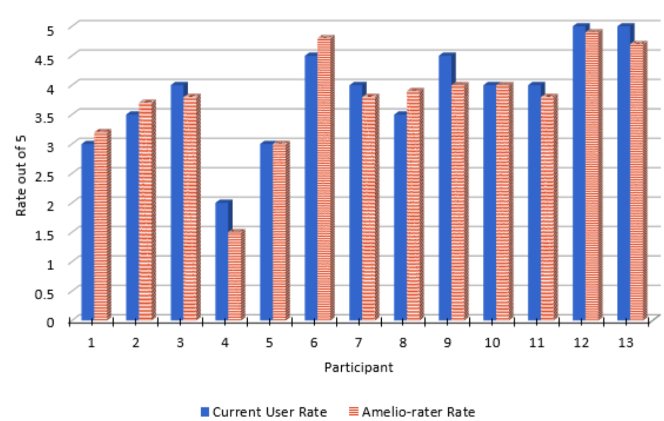

Fig. 5. Graph illustrating the manual current user rate against the automatically generated Amelio-rater rate for each participant.

The graph in Figure 5 visualises the results for the rating given manually to each participant against that generated by the Amelio-rater.

A Two-Sample assuming unequal variances was conducted to compare manual user rate and Amelio-rater rate. There was a no significant difference in the scores for manual user rate

	Predicted Value			
		Sudden Lane Change	Single Weaving	Meandering
Actual Value	Sudden Lane Change	TP	FN	FN
	Single Weave	FN	TP	FN
	Meandering	FN	FN	TP

TABLE II. MAPPING OF TP AND FN FOR DIFFERENT TYPES OF ABNORMAL DRIVING BEHAVIOURS

(M=3.85, SD=0.85) and Amelio-rater rate (M=3.78, SD=0.88); t (13)=0.20, p = 0.42. These results suggest that the Amelio-rater difference is considered to be statistically insignificant. The mean of manual user rate minus Amelio-rater rate equals 0.069, 95% confidence interval of this difference: From -0.634 to 0.772.

When a driver starts a trip, a car appears on a map on the business monitor's website. If more than 1 driver start a trip at the same time, all of them appear on the map with their current locations and abnormal behaviour. This is indicated by the colour of the car icon on the map.

When speeding, the driver should hear a beep. Even though the beep would be heard after a delay of up to 2 seconds.

2) Experiment 2 - Discussion: Each driver performed up to 20 abnormal driving behaviours in the trip. The Amelio-rater classifies an abnormal driving behaviour performed as one of the three trained behaviours. When an untrained abnormal driving behaviour is performed, it is classified as one of the 3 trained behaviours in the Amelio-rater using a pre-defined threshold.

	Sudden Lane Change	Single Weave	Meandering
Sudden Lane Change	-	✓	x
Single Weave	x	-	x
Meandering	x	✓	-

TABLE III. CONFUSION MATRIX BETWEEN BEHAVIOURS THROUGHOUT THE TRIPS PERFORMED IN THE EXPERIMENT

The participants in the experiments have stated that some confusion between different behaviours has occurred; however, normal driving behaviour was never misclassified as an abnormal behaviour nor the opposite. They have also stated that there was confusion at some point between different abnormal behaviours. As seen in Table III, Sudden Lane Change was misclassified as Single Weave, and Meandering as Single Weave as well.

According to Figure 6, speeding has been detected 77% of the time when driving normally, and 69% of the time when performing any of the abnormal driving behaviours. After the passenger finishes his/her trip a generated number from the Amelio-rater scaled out of 5 is shown to the passenger.

The subjects provide us with their manual rating before mentioning the Amelio-rater rating. The reason for this was to avoid any biased user rating. The manual ratings were usually lower than the Amelio-rater's. In both cases, there was a slight difference between both ratings.The subjects were satisfied with the ratings generated by the Amelio-rater. They also stated that having both rates assigned to the drivers will gives a better insight to the performance of the driver. Where the subjects can use the Amelio-rater rate to determine the driver's level of performance based on his driving style alone.

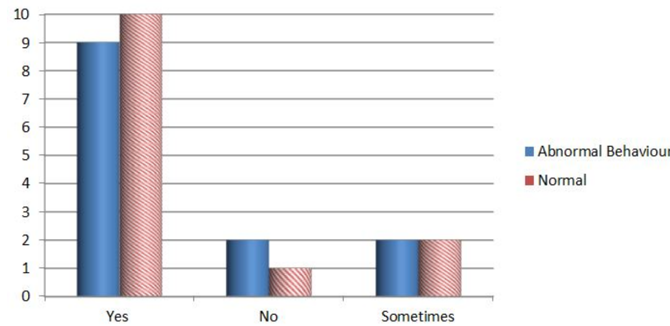

Fig. 6. Rate of detection of speed in a trip when driving normally and when performing an abnormal driving behaviour.

VI. CONCLUSION

Throughout the implementation of the Amelio-rater, we have faced some challenges. One of the main challenges that was faced is that the GPS sensor has a delay up to 10 seconds. Thus in the real time monitoring, the car that appears on the map would stay in the same position even though it is actually moving. This is because the rate of sending data to the database is faster than the rate of position update by the GPS. Another challenge is detecting that the driver is speeding based on the speed limit of the street at which (s)he is driving at that time. DTW classifier needs to have training datasets for each behaviour in order to classify it. Driving abnormal behaviours are infinite, not every case could be trained. The Amelio-rater is trained for three behaviours so far. Another challenge faced that was faced is what to do if a behaviour was done by the driver, and it is not normal nor is it one of the three trained behaviours. Throughout our experimentation, we aimed to enhance the classifier accuracy; until we finally achieved an accuracy of 95% when experimenting the classification of the abnormal driving behaviours in the real time. Amelio-rater rates were very close to the actual rates given by the users.

VII. FUTURE WORK

In the future, we would like to find solutions to the challenges mentioned above. For the GPS delay in location update, interpolation could be implemented to fill in the missing co-ordinates between each two position vectors. More behaviours could be introduced to the Amelio-rater, such as Sudden Braking, Fast U-Turns, and Turning with a Wide Radius. Finally, the sensor readings collected and stored could be used in some big data analytics to come up with analysis on road conditions. For instance, if an abnormal driving behaviour occurs continuously by different drivers in the same location then most probably there is a road anomaly in that area. Detection and classification of road anomalies such as road bumps and dents has been kept as a future work. Such information could be used in two ways: collect information about different road condition and enhance the Amelio-rater to not consider the behaviour as abnormal if it is due some road anomaly. We would also like to find a method to fuse the accelerometer sensor with the gyroscope sensor to reach a higher accuracy level. For the Amelio-rater rate to be enhanced, the latest trips performed by the driver should have a higher weight in the equation compared to the older ones. This will help have focus on the driver's current driving performance; whether s/he have improved or deteriorated.

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