# Performance comparison of dynamic time warping (DTW) and a maximum likelihood (ML) classifier in measuring driver behavior with smartphones

J. Engelbrecht, M.J. (Thinus) Booysen, G.-J. van Rooyen, F.J. Bruwer
Department of Electrical and Electronic Engineering
Stellenbosch University
Stellenbosch, South Africa, 7600
Email: mjbooysen@sun.ac.za

***Abstract*—The ubiquitous presence of smartphones provides a new platform on which to implement sensor networks for Intelligent Transport Systems (ITS) applications. Smartphone-based driving behavior monitoring has applications in the insurance industry, fleet management, driver training, and for law enforcement. In this paper we propose a Maximum Likelihood (ML) classifier to identify and classify the recklessness of driving maneuvers using the embedded sensors and GPS receiver of a smartphone. We compare the developed approach to the commonly used Dynamic Time Warping (DTW) based method. The solutions are both suitable for real-time applications, such as driver assistance and safety systems. An endpoint detection algorithm is used on filtered accelerometer and gyroscope data to find the start- and endpoints of driving events. The events are isolated with the endpoint detection algorithm are then classified using the DTW algorithm and an ML classifier. Results show that the ML classifier outperforms the DTW approach.**

## I. Introduction

Worldwide, more than a million deaths are caused by road accidents per year [1]. The World Health Organization predicts that road fatalities will rise to become the fifth leading cause of death by 2030 [1]. Research done in the United States shows that, in more than 50% of fatal road accidents, unsafe driving behaviors were involved [2]. Road accidents are caused by a variety of factors, but aggressive driving behavior is one of the major causes.

In the last decade, various companies have been developing solutions to monitor a vehicle and its driver's behavior [3]–[6]. However, these solutions are expensive and intended for fleet management, and there is little incentive for individuals to buy them. However, the increasingly ubiquitous presence of smartphones – with their variety of sensors – presents the possibility to easily implement vehicle monitoring systems on a large scale.

Most modern smartphones have a variety of embedded sensors — typically an accelerometer, gyroscope, microphone, camera and Global Positioning System (GPS) as well as light-, proximity- and magnetic sensors. This variety of sensors makes many sensing applications possible. An example of such an application is gesture recognition, which is used to answer a call when bringing the phone to one's ear, or paging through a document by the wave of a hand [7], [8]. Vehicle monitoring is an attractive sensing application for smartphones. For instance, drivers can be monitored to make them aware of their potentially dangerous driving behavior.

The existing works do not enable a fair comparison of the approaches, since the technologies used (mobile phones, sensors, software) and test conditions (maneuvers, drivers, roads) are different. This paper evaluates the performance of the ML classifier by comparing it to the commonly used dynamic time warping (DTW) algorithm with a heuristic method for classification . The evaluation uses a common dataset which is benchmarked against human experience of a common set of different maneuvers performed by different drivers. The performance of the innovatively implemented ML classifier can therefore be quantitatively compared to the commonly used DTW algorithm and heuristic classifier combination.

The remainder of this paper is organized as follows: Section II presents the current state of the art of smartphone-based monitoring systems; Section III describes the design of two proposed driving maneuver recognition systems; Section IV covers the approach to testing as well as the comparison of the two systems' results after testing; and Section V presents the concluding remarks.

## II. State of the art

In this section, a brief overview is given of the current literature on smartphone-based monitoring systems used in vehicles. The techniques and sensors used in the more recent projects are listed in Table I, and expanded upon in [9].

The literature distinguishes between driving maneuver recognition and driving behavior classification. A system could detect various maneuvers, but not necessarily infer anything from them, whereas another system may be able to classify a driver's behavior from detected driving maneuvers. These different systems demonstrate the variety of driving behavior classifications that can be made. A person's normal driving style can be classified as safe or risky, fuel-efficient or inefficient, skilled or unskilled — and recommendations can be given accordingly to improve their driving.

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TABLE I
SUMMARY OF TECHNIQUES AND SENSORS USED BY SMARTPHONE-BASED VEHICLE MONITORING SYSTEMS.

| Reference | Detection technique | Sensors used |
|---|---|---|
| Mohan [10] | pattern matching, orientation calibration | accelerometer, microphone, GPS |
| Dai [11] | pattern matching, orientation calibration | accelerometer, gyroscope |
| Johnson [12] | endpoint detection, DTW | accelerometer, gyroscope, magnetometer, GPS |
| Eren [13] | endpoint detection, DTW, Bayesian classifier | accelerometer, gyroscope, magnetometer |
| Fazeen [14] | pattern recognition | accelerometer, GPS |
| White [15] | pattern matching | accelerometer, microphone, GPS |
| Wahlstrm [16], [17] | theoretical tire slip threshold detection | GPS |
| Handel [18] | multiple figures of merit, threshold detection | GPS |
| Castignani [19] | fuzzy logic | GPS, accelerometer, magnetometer, weather, time of day |

Johnson and Trivedi [12] developed one of the first complete driver behavior monitoring systems on a smartphone. Their system can detect and classify a number of aggressive and non-aggressive driving maneuvers when placed in a vehicle, by only using the internal accelerometer, gyroscope, magnetometer and GPS of a smartphone. Although the system can identify aggressive driving maneuvers, it does not draw any conclusions about the aggressiveness level.

Eren et al. [13] also implemented a smartphone-based driving maneuver detection system similar to Johnson and Trivedi's [12] approach. However, they expanded the system by adding a driving style characterization feature that labels a person's driving style as either safe or unsafe with a given probability. Dai et al. [11] developed a smartphone-based system that specifically detects drunk driving. This is achieved by detecting and positively identifying a combination of dangerous driving maneuvers associated with drunk driving. Fazeen et al. [14] implemented a driver assistance system entirely on a smartphone. The system records and analyses various driver behaviors and external road conditions, and advises a driver on dangerous vehicle maneuvers using simple thresholding. Mohan et al. [10] developed a comprehensive road and traffic monitoring system, named Nericell, which also employs smartphone sensors to detect certain driving maneuvers and road conditions. Wahlström et al. [16] defined a dangerous cornering event relative to the thresholds where slipping or vehicle rollover are theoretically likely to occur. GPS measurements were filtered and processed to extract the tangential velocity, rotational velocity and tangential acceleration of the vehicle being monitored. From these variables, the instantaneous ratio between the horizontal and vertical forces on the vehicle can be calculated and compared to the ratio at the no-slip threshold. A fraction of the no-slip threshold at which a corner is deemed to be reckless was chosen empirically. In a second

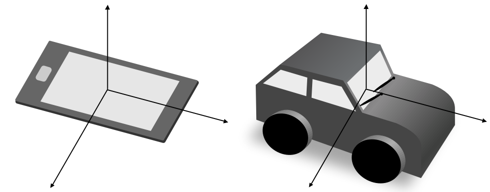

Fig. 1. Smartphone and vehicle coordinate system.

paper, Wahlstrm et al. [17] uses tangential velocity, tangential acceleration and turn radius instead of rotational velocity. The turn radius is estimated using a circle fitting technique to fit circles to position measurements. Castignani et al. [19] uses smartphone-based accelerometer, magnetometer and GPS sensors to identify and rate the riskiness of driving events. This is done by defining fuzzy logic sets for each parameter after a calibration phase in a specific vehicle. The relevant parameters chosen are the standard deviation of the Jerk(derivative of accelerometer measurement), mean yaw rate (using orientation sensors) as well as the speed and bearing variations (from GPS measurements). Vehicle-specific calibration is proposed, as different vehicles have unique driving characteristics.

### A. Contribution of this paper

Existing work presents methods for recognizing driver behavior using algorithmic approaches (such as simple thresholding or dynamic time warping (DTW)) or heuristic approaches. This paper covers the design and implementation of a suitable supervised machine learning classifier, namely the Maximum Likelihood (ML) classifier, to identify and classify driving maneuvers as aggressive or safe. The performance of the two approaches are compared in identifying maneuvers and classifying the severity thereof. The paper also presents an evaluation of combinations features that could be used to identify reckless driving.

## III. SYSTEM DESIGN

This section describes the detail design of the algorithmic DTW-based approach and the ML approach, which are used to identify driving maneuvers and classify them as either aggressive or not. Although DTW is used by various existing literature, its design is also detailed here to enable a comparison between the two approaches. The hardware setup used to collect driving data with which the system was developed and tested is also described.

The vehicle's axes are denoted as $x'$, $y'$ and $z'$ in the directions as shown in Figure 1. The smartphone's axes are denoted as $x$ pointing towards the right and $y$ to the top from the phone's front, while $z$ points out orthogonal to the page. The system assumes the smartphone's axes are aligned with the vehicle's axes, since existing work addresses this re-alignment [20]. Readings from the accelerometer's three axes $(x, y, z)$ are denoted as $a_x$, $a_y$ and $a_z$. Readings from the gyroscope's three axes are denoted as $\omega_x$, $\omega_y$ and $\omega_z$. Accelerometer readings are expressed in terms of the

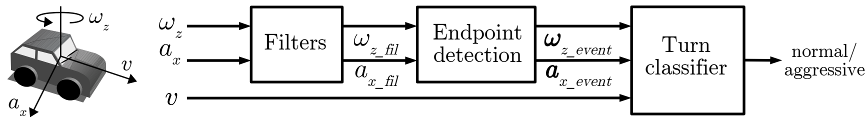


Fig. 2. Three inputs are used to identify and classify bends and maneuvers: $a_x$, rotation rate around its vertical axis, $\omega_z$, and forward velocity, $v$. Also shown is the system used to compare the Turn classifiers (DTW vs. ML)

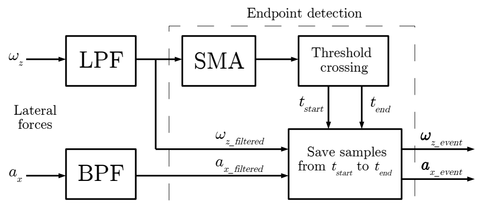


Fig. 3. Subdiagram of the detection algorithm before classification occurs.

acceleration from gravity, $g$ (9.8 m/s$^2$), and gyroscope readings in terms of rotation rate (rad/s).

### *A. Hardware setup*

A Samsung Galaxy S3 smartphone was used for driving data collection. A simple data logger Android application was developed that samples the accelerometer and gyroscope at 20 Hz, in accordance with [12]. Although a higher sampling rate is possible, it increases power consumption, and 20 Hz was considered fast enough for the proposed system. The application saves the sensor samples and GPS data to an SQLite database. In order to validate the smartphone's data, an Arduino board was used to also log data from a dedicated GPS and inertial measurement unit (IMU) to an SD card.

### *B. Aggressive driving model*

Aggressive driving is considered as deliberate behavior by a driver to perform any maneuver in such a manner that increases the risk of a road accident. The aggressive driving model we used is based on the angle of a turn, the lateral force exerted on the vehicle and it's speed through the turn [21].

The gyroscope, accelerometer and GPS of a smartphone is used accordingly to obtain the required information. Figure 2 presents a block diagram of the overall system used in the comparison. The system is designed to detect lateral maneuvers, or more specifically turns, and classify them as taken normally or aggressively. The diagram shows the three inputs of the system and their relation to the vehicle, namely the vehicle's lateral force of acceleration, $a_x$, rotation rate around its vertical axis, $\omega_z$, and its forward velocity, $v$. Using only these three inputs, the system must be able to detect and classify a turn based on previously provided hand-annotated training data. Taking in filtered data, the endpoint detection block outputs signal vectors to the turn classifier.

### *C. Endpoint Detection*

In order to detect maneuvers to be classified, the start and end of driving events are determined by using the endpoint detection algorithm. For lateral maneuvers, a simple moving average (SMA) of $\omega_z$ is continuously calculated over 40 samples. The beginning of a lateral event is detected if the SMA goes above a set threshold. The previous 40 and succeeding samples of $\omega_z$ are concatenated until the SMA falls below the threshold, signifying the end of the event. The samples of $a_x$ are also saved during the same time window. An event is dismissed if it is less than 2.5 or more than 15 seconds long. This is to keep the system from hanging on potentially erroneous or noisy data. The length boundaries were established empirically to detect most valid events.

### *D. Recognition algorithms*

The DTW and ML methods are detailed and developed in this section. The first method uses DTW to compare detected events to driving maneuver templates, and then uses the results in a simple heuristic to classify the maneuver as safe or reckless. The aim is to reproduce on equal footing the DTW approaches found in existing literature. The second method uses supervised learning to train an ML classifier to label driving maneuvers. The ML classifier was chosen as it was found to be the most suitable supervised learning classifier for the recognition of aggressive driving. Figure 2 shows a block diagram of the system. The DTW and ML approaches are implemented as the turn classifiers and compared in this paper in the system. The accelerometer output is band-pass filtered to remove sensor noise and the gravitational force vector, as its direction changes slowly when the vehicle's roll and pitch changes while driving. The gyroscope output is low-pass filtered to remove noise. The filtering and endpoint detection used for both DTW and ML are shown in Figure 3.

*1) Dynamic Time Warping:* The DTW approach is based on the work of Johnson and Trivedi [12], and Eren et al. [13].

When a valid driving event has been detected, the signals recorded during the event are compared to a set of templates using the dynamic time warping (DTW) algorithm [22]. DTW finds an optimal alignment between two time-dependent sequences with different lengths. The template with the lowest minimum-distance warp path to the detected event is the closest match.

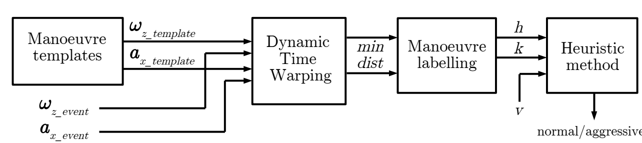


Fig. 4. Subdiagram of the DTW classification approach.

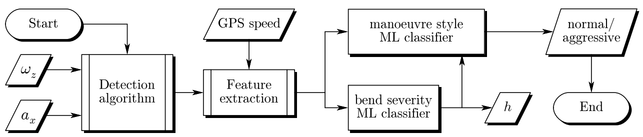


Fig. 5. Flow diagram of the Maximum Likelihood (ML) classifier.

The acceleration and rotation rate templates are discrete Gaussian signals with fixed lengths that were created from collected driving data with multiple drivers. The $\omega_z$ templates indicate the angle of a turn. It allows the system to classify the severity of a left or right bend (i.e not the action of turning, but measuring the physical curvature of the road) from 1 to 3, based on the closest matching $\omega_z$ template — with 1 indicating an easy bend, 2 a medium bend and 3 a sharp bend. Similarly there are six $a_x$ templates with increasing amplitudes.

A heuristic method is used to label any recognized turn as taken normally or aggressively, based on the vehicle's speed (obtained from the GPS) and matching $a_x$ and $\omega_z$ template. From experimental results it was evident that two conditions need to be satisfied to classify a turn as aggressive:

$$\begin{array}{ll} 1. & v > 50(3-h) \\ 2. & k > 4 \vee k > (h+2) \end{array}$$

where $v$ is the vehicle's speed in km/h, $h$ is the bend severity (1–3) (measured by the gyroscope) and $k$ is the lateral acceleration defined by the template number (1–6) of $a_x$.

*2) Maximum Likelihood:* Maximum likelihood (ML) estimation is an algorithm that estimates (or *learns*) the parameters of a statistical model. The set of parameters $\hat{\boldsymbol{\theta}}$ under which the data $\{\mathbf{x}_i\}_{i=1}^{I}$ are most likely is equal to the product of the likelihood functions at each individual data point $\mathbf{x}_i$. The likelihood function $P(\mathbf{x}_i|\boldsymbol{\theta})$ is obtained by assessing the probability density function at $\mathbf{x}_i$. The maximum likelihood estimate of the parameters therefore is

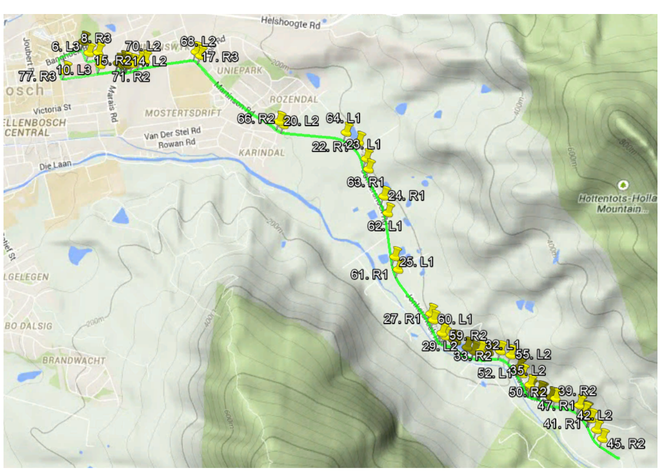


Fig. 6. The route driven by each participant, showing all the hand-annotated bends.

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \left[ \prod_{i=1}^{I} P(\mathbf{x}_i|\boldsymbol{\theta}) \right], \tag{1}$$

where $\operatorname{argmax}_{\boldsymbol{\theta}} f[\boldsymbol{\theta}]$ returns the value of $\boldsymbol{\theta}$ that maximises the argument $f[\boldsymbol{\theta}]$.

After the parameters $\hat{\boldsymbol{\theta}}$ of a model have been determined, they can be used for binary classification of new data. For this purpose, a training data set with selected features and class labels was pre-processed from collected driving data. It was used for supervised learning of two separate maximum likelihood classifiers. The first classifier is trained to label the severity of a bend. The second classifier is trained to label a turn as taken normally or aggressively. The trained classifiers can be used to label driving manoeuvres immediately after they are detected in a real-time system. Figure 5 shows a flow diagram of the maximum likelihood classification method.

To reduce the computational load caused by performing maximum likelihood classification, feature extraction is first performed on the angular velocity ($\omega_z$) and lateral acceleration ($a_x$) signals of an event detected by the endpoint detection. Coefficients of fifth order curve fitting to $\boldsymbol{\omega}_z$ were used for bend severity classification , with outputs of $h = 1, 2, 3$. As an example, figure 7 shows the results of fitting 5th-order polynomial curves to the accelerometer and gyroscope's signals of detected turns. Examples of a severity 2 and 3 bend, each taken both normally and aggressively, are given. The fitted curves generally match the signals quite well and can be considered as a good representation.

Various combinations of selected features were tested to find the best representation of normally versus aggressively taken turns. The list of tested features taken from both the accelerometer and gyroscope signals are:

- Polynomial curve fitting coefficients.
- Minimum, average and maximum amplitudes.
- Minimum peak to maximum peak amplitude.
- Signal energy.
- Fundamental frequency and its magnitude.
- Integral of gyroscope signal as estimation of rotation.

Also consider that, between the normally and aggressively taken turns, there is a notable difference in the peak acceleration, but not in the peak rotation rate. Amplitude features from the accelerometer signal are therefore usable, but not from the gyroscope signal. Signal energy is defined as

$$E_{\mathbf{x}} = \frac{T}{N} \sum_{n=0}^{N-1} |x[n]|^2 \quad , \tag{2}$$

where $T$ is the duration of the signal and $N$ the number of samples. From Figure 7 it can also be seen that the accelerometer signal energy is more for an aggressive turn than a normal turn by looking at the peak amplitude.

The list of tested features taken from both the accelerometer and gyroscope signals are extracted from event data, and these

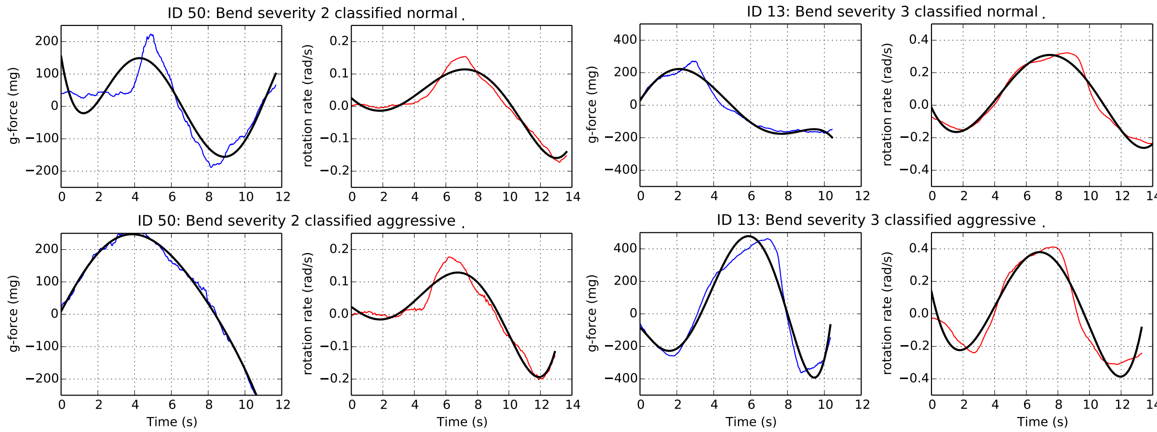


Fig. 7. Curve fitting to the accelerometer and gyroscope signals for specific bends taken normally and aggressively.

features are also normalized using the minimum and maximum values from the training data set, as shown in equation 3.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad , \tag{3}$$

The vehicle's GPS speed is also used as an additional input. A representational feature vector is then given as input to the two classifiers for bend severity and driving style classification.

## IV. Experimental Setup

Six individuals were asked to drive a pre-determined route while subjective labelling of their turns were performed by hand. A route of 15 km was chosen that has varying bends and up- and downhill parts. The route necessitates drivers to manage their speed as straighter sections are followed by several sharp bends. A map of the route is shown in Figure 6. All the distinct bends were annotated by hand on a map with a severity of 1, 2 or 3 – this was done for testing, and for training of the ML approach, and will be needed in the eventual installation. The route has 55 identified bends — 28 right and 27 left bends.

Preliminary data was recorded with the smartphone, dedicated IMU and u-blox GNSS receiver in a fixed position and orientation in the vehicle. The smartphone's and IMU's axes were aligned to the vehicle's axes. A standard front-wheel drive sedan was used. The preliminary data was needed to test the accuracy of the smartphone's sensors and the reliability of the Android application. The u-blox's data was specifically used to validate the accuracy of a high-pass filter in removing the gravitational acceleration vector from accelerometer data. It was also used for sanity testing during the system development. The six participants each drove the route once or twice for the training and test data set. They each drove in their own vehicle to ensure familiarity and a normal driving style. A form with all the identified bends in sequential order was used for each run. Route notes were used to label how the driver took each bend: normally or aggressively. Although the labelling was done subjectively, it was kept consistent for each driver.

The raw data was post-processed and valid data was successfully extracted and labelled for 387 bends. Overall, the endpoint detection algorithm successfully detected 95% of the left and right bends. The data was split in a 66%/33% ratio for training and test data respectively. The training data set was used to create gyroscope and accelerometer signal templates for the three bend severities taken both normally and aggressively. Twelve templates were thus created from the gyroscope and accelerometer data in total.

## V. Results

The test data set was used to obtain the results given in Table III. For the driver labeled as the most aggressive from observation, the classifier achieved a FN and FP rate of 80% and 10.5%, respectively.

With 24 out of 129 turns in the test set being aggressive, the turn labelling heuristic achieved a FN and FP rate of 62.5% and 4.8%, respectively. Although the FN rate is high, a lower FP rate is desirable. It is biased to label a driver as aggressive based on falsely identified aggressive maneuvers. The heuristic was empirically tuned to obtain the least false positives, at the expense of missing true positives (TP).

*3) Supervised Machine Learning:* Table II shows the performance measures obtained by using different combinations of features for aggressive maneuver classification. For the sake of simplicity, minimum, average and maximum amplitudes are not used, as it was found that peak-to-peak amplitude, on its own, always resulted in better performance than any combination of amplitude features. The results also show that, as expected, the fundamental frequency magnitude is a better feature than the fundamental frequency itself. Given these results, the peak-to-peak amplitude $\mathbf{a}_{x(pk-pk)}$, energy $E_{\mathbf{a}_x}$, and $f_0$ magnitude of the accelerometer signal, as well as the $f_0$ magnitude of the gyroscope signal, the GPS speed $v$, and output of the bend severity classifier $h$, are selected as the best feature set.

TABLE II
PERFORMANCE MEASURES (%) OF DIFFERENT COMBINATIONS OF FEATURE SETS FOR AGGRESSIVE TURN CLASSIFICATION.

| **Precision** | **Recall** | **Specificity** | **Accuracy** | $\mathbf{a}_x$ $_{pk-pk}$ | $E_{\mathbf{a}_x}$ | $v$ from GPS | $h$ $h$ | $f_0$ mag of $\mathbf{a}_x$ | $f_0$ of $\mathbf{a}_x$ | $f_0$ mag of $\boldsymbol{\omega}_z$ | $f_0$ of $\boldsymbol{\omega}_z$ | Area of $\boldsymbol{\omega}_z$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 75 | 50 | 96 | 88 | × | × | × | × | × | | | | |
| 80 | 50 | 97 | 88 | × | × | × | × | × | | | × | |
| 86 | 50 | 98 | 89 | × | × | × | × | × | | × | | |
| 75 | 50 | 96 | 88 | × | × | × | × | × | | | | × |
| 79 | 46 | 97 | 88 | × | × | × | × | × | | × | | |
| 56 | 42 | 92 | 83 | × | × | × | | × | × | | | |
| 70 | 67 | 93 | 88 | × | × | × | | | × | | | |

TABLE III
DYNAMIC TIME WARPING CLASSIFICATION RESULTS.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Bend severity classification: | | | | | | | |
| Accuracy | = 83.7% | | | | | | |
| Aggressive maneuver classification: | | | | | | | |
| Precision | = 64.3% | | | | | | |
| Recall | = 37.5% | TP | FP | = | 9 | 5 | |
| Specifity | = 95.2% | FN | TN | | 15 | 100 | |
| Accuracy | = 84.5% | | | | | | |

TABLE IV
MAXIMUM LIKELIHOOD CLASSIFIER RESULTS.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Bend severity classification: | | | | | | | |
| Accuracy | = 91.5% | | | | | | |
| Aggressive maneuver classification: | | | | | | | |
| Precision | = 77.8% | | | | | | |
| Recall | = 58.3% | TP | FP | = | 14 | 4 | |
| Specifity | = 96.2% | FN | TN | | 10 | 101 | |
| Accuracy | = 89.1% | | | | | | |

Table IV shows the results of the ML classifier on the test data set. The ML bend severity and aggressive maneuver classifiers obtained an accuracy of 91.5% and 89.1%, respectively. That is 7.8% and 5.2% higher than the DTW based classifier's accuracy. The ML aggressive maneuver classifier obtained a recall of 58.3% and specificity of 96.2%. The ML classifier's recall, is comparatively a significant improvement over that of the DTW based classifier. More importantly though, the precision of the ML classifier is substantially better than the DTW classifier's, 77.8% compared to 64.3% for the DTW classifier.

The results for the most aggressive driver are 40% and 10.5% for the FN and FP rate, respectively. The ML classifier obtains half the FN rate of the DTW classifier, while maintaining the same FP rate, which is a significant improvement. It is evident from these results that the ML classifier is superior to the DTW algorithm at classifying aggressive maneuvers.

## VI. ACKNOWLEDGEMENTS

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## VII. CONCLUSIONS

This paper presents and compares two driving maneuver recognition and classification systems that are suitable for implementation on a smartphone. The recognition algorithms can both successfully detect turns of varying severity using either dynamic time warping or a maximum likelihood classifier. The systems can also label each recognized turn as taken normally or aggressively by the driver. The systems are both expandable to recognize a variety of maneuvers. The maximum likelihood classifier, however, showed significantly better results than that of the DTW algoritm. The system could be used to monitor a driver and provide driving safety related feedback to the driver or provide actuarially relevant feedback to an insurance company to be used as a metric for premium adjustment. The prevalence of smartphones also allows such a system to be easily and cost-effectively deployed on a large scale. In future work the system can be expanded to recognize further maneuvers, such as harsh breaking, rapid accelerations and swerving. Much work can also be done on improving the energy efficiency of the system.

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