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Leveraging Sensor Information from Portable Devices towards Automatic Driving Maneuver Recognition

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Abstract— **With the proliferation of smart portable devices, more people have started using them within the vehicular environment while driving. Although these smart devices provide a variety of useful information, using them while driving significantly affects the driver's attention towards the road. This can in turn cause driver distraction and lead to increased risk of crashes. On the positive side, these devices are equipped with powerful sensors which can be effectively utilized towards driver behavior analysis and safety. This study evaluates the effectiveness of portable sensor information in driver assistance systems. Available signals from the CAN-bus are compared with those extracted from an off-the-shelf portable device for recognizing patterns in driving sub-tasks and maneuvers. Through our analysis, a qualitative feature set is identified with which portable devices could be employed to prune the search space in recognizing driving maneuvers and possible instances of driver distraction. An absolute improvement of 15% is achieved with portable sensor information compared to CAN-bus signals, which motivates further study of portable devices to build driver behavior models for driver assistance systems.**

I. INTRODUCTION

Although driving might be considered an obvious habit, even the slightest lapse in driver's attention can potentially lead to a near-crash/crash with varied levels of intensity. Results from the 100-car Naturalistic Study showed that over 75% of crashes and 65% of near-crashes were caused due to driver inattention [1]. National Highway Transport Safety Administration (NHTSA) has identified the use of portable electronic devices within the vehicular environment as one of the primary causes for driver inattention and driver distraction [2]. Portable tablets and smart mobile phones fall in this category.

Recent years have seen a proliferation in smart portable devices such as mobile phones and tablets which are equipped with a wide range of sensors from inertial measurement units (IMU) (e.g., accelerometer and gyroscope) to magnetometer and GPS receivers. These sensors, which are included mainly for better gaming and user experience, along with better and larger display, user interface, and constant data connectivity make portable devices highly desirable. Drivers generally use smart portable devices for listening to music, navigation assistance, weather assistance, accessing internet, and of course for communication over the phone. These tasks are attention seeking and, if performed while driving, could deviate driver's attention from the road for a prolonged period leading to a near-crash/crash. Even though new laws have recently been passed to prohibit the use of portable devices while driving, with so many new features and applications, it is becoming more difficult to define the boundary within which these devices can be operated.

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Over the past few decades, the automotive industry has made tremendous advancements in increasing the safety of vehicles and their occupants. From seat belts, air bags and anti-lock braking systems (ABS) to Embedded Stability Program (ESP), Forward Collision Warning (FCW) and Collision Mitigation by Braking (CMBB), there are advanced safety systems in the cars which constantly monitor the vehicle and surrounding environment to ensure occupant safety. This has been made largely possible by a robust network which connects sensors, embedded systems and actuators within the vehicle to form a complete system. This network, which is called the Controller Area Network (CAN) [3], carries all signals and information concerning the present state of the vehicle. Valuable signals such as vehicle speed, steering wheel angle, gas and brake pedal pressures are available on this network bus, and henceforth in this study will be addressed collectively as CAN-bus signals.

In spite of all the useful data available on the CAN-bus, only a small portion of it is made accessible to the outside world through an On-Board Diagnostic (OBD) port. The available data mainly helps in troubleshooting as well as obtaining vital information about the vehicle. The rest of the CAN-bus data is, however, encrypted and restricted from direct access, making it challenging for researchers as well as commercial developers to implement, test, and deploy advanced safety features in vehicles without the help and support of car manufacturers. Therefore, it is worthwhile to explore alternative sources of information which could be utilized for active safety in vehicles.

Towards this goal, in this study, we investigate the effectiveness of sensor information extracted from an off-the-shelf smart portable device for driving event recognition. In order for active safety systems to provide proper assistance to drivers, it is of great importance to detect and track different driving maneuvers. Research in driving maneuver recognition is not new [6], [7], [8], [9], [10], and several researchers have used CAN-bus signals and obtained over 90% accuracy for this task [6], [9]. However, given the challenges in accessing CAN-bus information, in [7] the use of IMUs for maneuver recognition was investigated and shown to be promising with a high accuracy near 95%. In addition, the application of portable systems in vehicle safety systems was suggested in [11], and more recently

[12], [13] adopted smart portable devices to detect driving style and drunk driving. This trend suggests that the sensor loaded portable devices have the potential for being adopted in driver assistance systems.

Rather than limiting the sensors being used, in this study, effort has been made to assess the effectiveness of all available sensors in a smart portable device towards detecting 8 distinct driving maneuvers. The performance is compared against that obtained with available CAN-bus signals. Thus, the main motivation in this paper is two-fold: 1) to assess whether smart portable devices can be used to detect driving maneuvers, and 2) to identify an efficient feature set or sensor information for reliable and robust maneuver recognition in vehicles.

II. SETUP AND DATA DESCRIPTION

To understand and develop safety systems, it is very important to analyze how the vehicle, driver and environment interact. In this regard, multimodal data acquisition platforms play a crucial role in synchronously acquiring and recording sensor information from all these modalities. For automotive research purposes, it becomes very helpful to instrument a particular vehicle with various sensors and recording platforms. Generally termed as “Instrumented Vehicle” – it provides reliable synchronized information to analyze data and develop new algorithms and systems. One such instrumented vehicle is from the UTDrive project [14], [15].

A. UTDrive Instrumented Vehicle

The UTDrive project was part of an international collaboration for collecting large-scale vehicle corpora and carrying out research on driver behavior and driving characteristics [14], [15]. A 2006 Toyota RAV4 was instrumented (see Fig. 1) with various sensors such as:

- 2 cameras, one facing the driver, another facing the road.
- A microphone array and a close talk microphone to capture both driver and other in-vehicular speech activity.

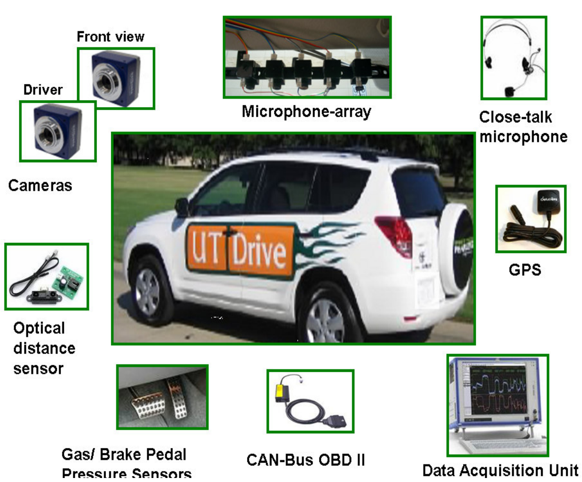

Fig. 1. UTDrive instrumented vehicle with available sensors.

Fig. 2. Inside of the UTDrive instrumented vehicle along with the portable device mounted on the windshield.

- Gas and brake pedal pressure sensors to capture the pressure with which driver hits the gas/brake pedals.
- GPS for location information.
- Distance sensor to measure distance to the vehicle ahead.
- CAN-bus signals are accessed and decoded to obtain signals such as vehicle speed, steering wheel angle, engine RPM, and brake/gas pedal pressure.

All these signals were synchronously recorded using a Dewetron (DA 121) data acquisition unit. More details on this instrumented vehicle can be found in [14], [15]. Over 100 drivers have driven the UTDrive vehicle on pre-defined routes under real traffic conditions. Data collected from different modalities and the research through the UTDrive project have provided a good insight into various driver and driving characteristics [4], [6]. However, instrumenting and maintaining the vehicle requires technical skills, and is also expensive.

B. UTDrive Portable Device

As a motivation to move from a fixed instrumented vehicle, portable devices offer a feasible alternative. Similar to the UTDrive instrumented vehicle, a typical off-the-shelf portable device would have sensors such as:

- Cameras (generally front and back)
- Microphones
- GPS
- 3-axis accelerometer
- 3-axis gyroscope
- Digital compass (Magnetometer)
- Ambient light sensor
- Proximity sensor

The 3-axis accelerometer and gyroscope can be employed to capture and analyze overall vehicle movements. Several research efforts [7], [12], [13] have shown that IMUs are useful in capturing vehicle movements. With these sensors contained within a portable device, it can effectively replicate the role of an instrumented vehicle.

In order to investigate the effectiveness and accuracy of the portable device platform in capturing vehicle movements, an application was developed on a Samsung Galaxy Tab™ 10.1 to record all available sensor information synchronously along with audio and video. The tablet was mounted in the instrumented UTDrive car as shown in Fig. 2. The developed application has been implemented on Android platform.

C. Route and Data Description

To analyze, characterize and recognize different driving maneuvers, the UTDrive instrumented car along with the portable device is driven multiple times by multiple drivers. To facilitate easy transcription and consistency in this study, two fixed routes as seen in Fig. 3 are driven both in clockwise and counterclockwise directions. The routes are selected such that it includes different road speeds as well as different traffic conditions. Each route takes approximately 7-9 minutes to complete.

The GPS on both devices (i.e., UTDrive and the portable device) help mark boundaries for known maneuvers such as turns, road curves, and stops. For lane change maneuvers, 2 independent transcribers visually look at the video and label the lane change boundaries. In this study, the following maneuvers are considered: Right Turn (RTR), Left Turn (LTR), Right Lane Change (RLC), Left Lane Change (LLC), Right Road Curve (RRC), Left Road Curve (LRC), Straight (STR), and Stop (STP). Turns could occur at any angle (not necessarily at 90 degrees), which are generally characterized by intersections or sharp bends on the road. On the other hand, road curves are generally smooth bends or transitions on the road.

D. Sensors Used

As listed in Section II (A and B), synchronously recorded signals from all modalities are stored. However, since this study focuses on maneuver recognition using signals from CAN-bus as well as sensor information from portable devices, we only utilize the signals and sensors of interest.

Fig. 3. Two separate routes selected with turns, road curves, stops and straight segments.

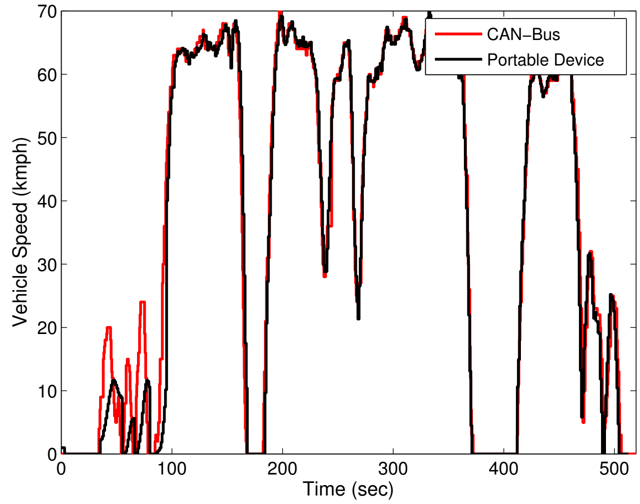

Fig. 4. A comparison of vehicle speed obtained from GPS of portable device and vehicle speed sensor from CAN-bus.

Video recordings are used for manual transcription of different maneuvers. Because GPS latitude and longitude are adopted for transcription in addition to video, they are not used for maneuver recognition.

As discussed earlier, only a limited set of CAN-bus signals could be tapped out and decrypted from the OBD port. Without the car manufacturer's support, we have been able to extract vehicle speed, steering wheel angle, engine RPM, and gas/brake pedal pressure information from the OBD port. We have already shown that these primary signals have sufficient information about driver/driving conditions [4], [5].

In addition to the primary sensors available from the portable device, a variety of useful information can be extracted from sensor fusion. In total there are 8 vehicle dynamics related sensors or sensor information which we employ in our experiments:

- 3-axis accelerometer – measures the acceleration applied on the device (or in this case the vehicle). Here, we are only interested in the lateral and longitudinal acceleration.
- 3-axis gyroscope – measures the angular speed or rotation around the device's local axis. Turns and vehicle swaying information can be computed using this sensor.
- GPS – along with latitude, longitude, it provides information about the vehicle bearing and vehicle speed.
- 3-axis magnetometer – measures the ambient magnetic field in each of the axes.
- 3-axis orientation – measures the orientation.
- 3-axis gravity – from which information regarding the magnitude of gravity in each direction is extracted.
- 3-axis linear accelerometer – which provides information similar to that provided by 3-axis accelerometer, with the gravity component removed.
- 3-axis rotation vector – measures the orientation of the device with respect to a fixed orientation.

All these sensors and derived sensor information are captured at the fastest rate (approximately 50 Hz) and down sampled to 1 Hz (via the standard procedure) to smooth out undesired noisy transient fluctuations which are mainly due to vehicle and car mount vibrations. In this manner, abnormalities in the signal are filtered out and only information pertaining to vehicle movements and maneuvers are retained.

Fig. 4 shows an example of the scaled and aligned vehicle speed captured independently from the CAN-bus (red) and the portable device (black). Since the GPS takes a while to lock-on, the initial values might not match but there is a high correlation between the two signals once the GPS data is locked-on. A similar match was shown in [12] between lateral accelerations captured from the CAN-bus and portable device.

E. Features Used

There are 5 signals which we were able to extract from the CAN-bus and 23 signals from the Portable device (7 $\times$ 3-axis data + vehicle speed and bearing information from GPS), making it a total of 28 signals which will be used for the maneuver recognition task. Since it is an exporatory analysis, rather than selecting only the relevant signals, all available signals are utilized here, and after feature selection we segregate only the most discriminative features and use them for further processing.

Motivated by previous successful work in [16], [17], an exhaustive list of statistical features is extracted from these 28 signals. Mostly extracted from the temporal signal, statistical features are straight forward to understand and extract in real-time processing. Along with static features, the dynamics (time derivative) of these signals often bear useful information regarding the vehicle maneuvers. For example, taking derivative of the longitudinal acceleration yields "vehicle jerk" which provides information about the driver's intention for any quick or evasive maneuver. A set of 15 distinct features and their descriptions are listed in Table 1. The first 10 features from amp to rms are extracted from both static and dynamic signals and the last 5 features are extracted only from static signals. Accordingly, overall there are 25 features selected for each of the 28 signals which sum up to 700 different features for the maneuver recognition task. Out of these 700 features, 125 features are from CAN-bus signals and the remaining 575 features are from the portable device.

TABLE I

FEATURES CONSIDERED AND THEIR DESCRIPTION

Feature	Description
amp	Difference between the maximum and mean value of the signal
namp	Difference between the mean value and minimum of the signal
med	Median of the signal
mean	Mean of the signal
min	Minimum value of the signal
max	Maximum value of the signal
p2p	Difference between the maximum and minimum value of the signal
std	Standard deviation of the signal
var	Variance of the signal
rms	Root mean square value of the signal
s2e	Amplitude of the difference between the first and the last samples of the signal
lpE	Variance of error in a 10^{th} order linear prediction (LP) analysis
ent	Entropy of the signal
dcVal	DC value of the signal
energy	Energy of the signal

III. Experimental Setup

Driving event or maneuver recognition forms one of the key components in analyzing driving characteristics and modeling driver's behavior for developing active safety systems. In this study, 8 different maneuvers are considered including RTR, LTR, RLC, LLC, RRC, LRC, STR and STP. These maneuvers are executed with varying time durations, ranging from 3-5 seconds for lane changes to 5-9 seconds for turns. Stops are typically driver and traffic dependent and can range from 5-15 seconds, whereas straight segments are mainly road dependent and can range from 15-30 seconds to 3 minutes. The durations noted here are based on the samples collected for this study, but they can vary drastically based on the geography as well as the time/date of driving among other factors. In our dataset, there are no maneuvers greater than 30 seconds and in case of straight segments, if the maneuver exceeds 30 seconds it is treated as a new straight segment. In our evaluations (including training and test phases) there are 816 maneuvers including all the 8 different types. Specifically, there exist 84 RTR, 91 LTR, 103 RLC, 108 LLC, 67 RRC, 60 LRC, 236 STR and 67 STP maneuvers.

As mentioned, our goal is to evaluate the effectiveness of sensor information extracted from the portable device in the context of a driving maneuver recognition task. Performance is compared against that obtained using available CAN-bus data. We employ two distinct type of classifiers namely k–nearest neighbor (k–NN) algorithm and support vector machines (SVM). The k–NN algorithm, which classifies objects based on a majority vote of its closest training examples, is used with $k = 7$. The SVM, which is a much more sophisticated method than the k–NN, is a binary classifier that makes its decision by constructing an optimal separating hyperplane (OSH) that divides a d-dimensional real space into two half spaces with the largest margin [18]. In order to perform multi-class classification with the SVM, two strategies are commonly adopted – one-versus-one and one-versus-rest. In our experiments we use SVM along with a Gaussian radial basis function (RBF) kernel and the one-versus-rest strategy. Since we have used all the available signals and sensor information from the two platforms to form an exhaustive feature set (i.e., 125-dimensional for CAN-bus, and 575-dimensional for the portable device), it is desirable to reduce the dimensionality of features before classification. Dimensionality reduction can be accomplished

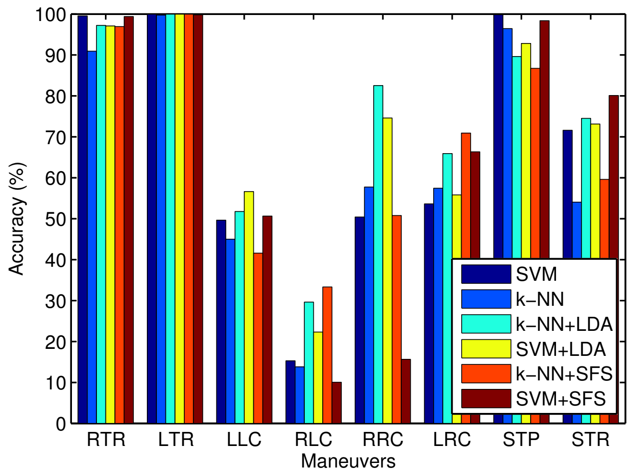

Fig. 5. Maneuver recognition accuracies using only features from CAN-bus signals with the different classifiers and dimensionaly reduction methods.

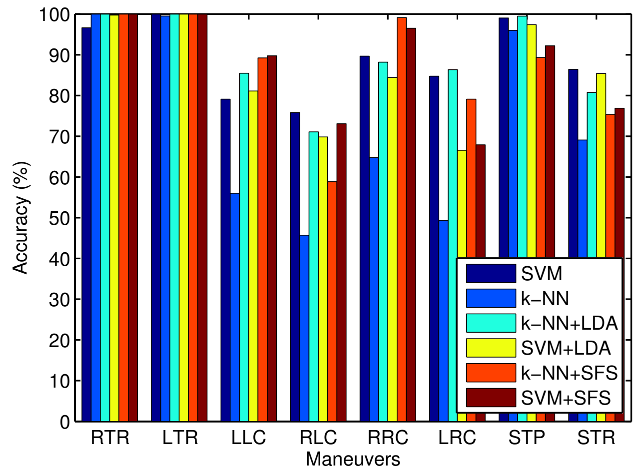

Fig. 6. Maneuver recognition accuracies using only features from the portable device sensor information with the two classifiers.

through either feature transformation or feature selection. In this study, the linear discriminant analysis (LDA) is used for feature transformation, while the forward sequential feature selection (SFS) is utilized for selecting the most influential subset of the features. Forward SFS is a process in which features are sequentially added to an empty candidate set until the addition of further features does not decrease a predefined criterion. Here, the mis-classification rate is adopted as the criterion.

Finally, to ensure generalized experimental outcomes that are not data/driver dependent, evaluations are carried out using a 10-fold cross-validation scheme. Results are obtained by averaging over 50 iterations of the cross-fold validation.

IV. RESULTS AND CONCLUSIONS

Comprehensive results of the maneuver recognition task are shown in Fig. 5 and 6 for CAN-bus and portable device features, respectively. The highest recognition performance is obtained with all the portable device features and the SVM classifier which yield a high accuracy of 89% (compared to 68% accuracy obtained with all the CAN-bus features). This supports our hypothesis that portable devices could be effectively used for the maneuver recognition. Since extracting and utilizing all feature may not be practical in real-time processing, we employ dimensionality reduction techniques. First, the LDA is used to reduce the dimensionality to 7 (number of classes minus 1). It is observed that the recognition performance with the CAN-bus features is improved significantly after the dimensionality reduction, and the *k*–NN classifier yields a high accuracy of 74%. For the same setup, the portable device features maintained the accuracy at 89%.

The results from the dimensionality reduction show that there is redundancy in the original feature set. It is very useful to identify an influential subset in the features which might be sufficient for maneuver recognition. This is accomplished via the sequential features selection approach which results in a 10-dimensional feature subset for the CAN-bus and a 16-dimensional feature subset for the portable device.

It can be seen from Fig. 5 and 6 that even with a small set of influential features a comparable performance is achievable. The 10-dimensional feature subset of the CAN-bus includes 4 feature from steering wheel angle (median, mean, peak-to-peak and entropy), 2 from gas pedal pressure (mean and rms), 2 from brake pedal pressure (mean and median of derivative), 1 from vehicle speed (LP error), and 1 from engine RPM (peak-to-peak of engine rpm derivative).The 16-dimensional features subset of the portable device contains 5 features from accelerometer (amp, median, and s2e of x-axis, rms of y-axis, and median of z-axis derivative), 4 from linear accelerometer (median and rms of x-axis, mean of its derivative, and std of y-axis), 3 from pitch-gyroscope (mean, peak-to-peak, and entropy), 3 from speed-GPS (derivative of speed, std, and LP error), and 1 from x-axis of gravity (entropy). As can be noted from both set of features selected, they are dependent not only on how the vehicle moves, but also on how the driver maneuvers the vehicle.

Fig. 7 compares the maneuver recognition accuracies of the best configuration for the portable device and CAN-

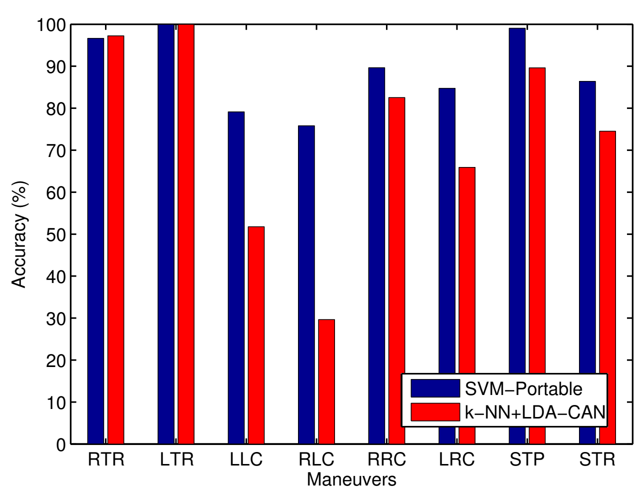

Fig. 7. A comparison of maneuver recognition accuracies from the best configuration obtained from Portable device and CAN-bus signals.

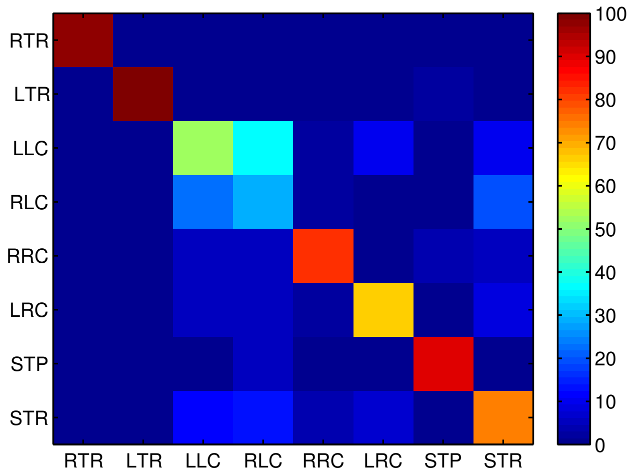

Fig. 8. Confusion matrix for maneuver recognition obtained from CAN-bus features with LDA and *k*–NN classifier.

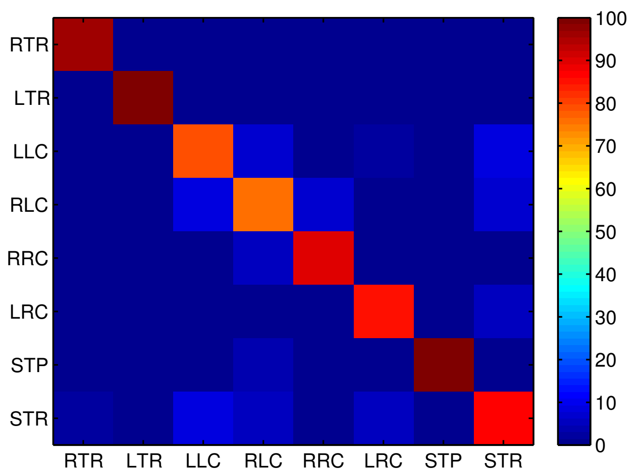

Fig. 9. Confusion matrix for maneuver recognition obtained using all the features from the portable device with the SVM classifier.

bus signals. It can be clearly seen that higher accuracies are obtained with the portable device sensor information compared to the CAN-bus signals.

Fig. 8 and 9 illustrate confusion matrices for the same configuration in Fig. 7. It is evident that most of the confusion lies in detecting lane changes, however, they are still more accurately detected using the portable device data. During RLC, many drivers maintain their speed and maneuver smoothly from a fast to a slower lane, thus making it more difficult to distinguish this maneuver from STR or LLC. LLCs are relatively easier to distinguish as drivers tend to increase their speed and maneuver swiftly from a slower to a fast lane.

As shown, the portable device proves useful in driving maneuver recognition. This opens new avenues for replacing expensive instrumented vehicles with off-the-shelf portable devices. It also obviates the need to be constrained to depend on car manufacturers for the proprietary CAN-bus information. It is worthwhile remarking here that this study does not de-emphasize the effectiveness of CAN-bus signals or makes any effort to replace the robust CAN-bus which serves as the backbone for most of the vehicular communication. It only shows that alternative platforms can be used towards driver assistance systems.

Another significant contribution of this study is that, from a exhaustive statistical feature set a much smaller set of discriminative features are selected which can be used for robust and effective maneuver recognition.

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