

Automatic Maneuver Boundary Detection System for Naturalistic Driving Massive Corpora

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ABSTRACT

Towards developing of advanced driver specific active/passive safety systems it is important to be able to continuously evaluate driving performance variations. These variations are best captured when evaluated against similar driving patterns or maneuvers. Hence, accurate maneuver recognition in the preliminary stage is vital for the evaluation of driving performance. Rather than using simulated or fixed test track data, it is important to collect and analyze on-road real-traffic naturalistic driving data to account for all possible driving variations in different maneuvers. Towards this, massive free style naturalistic driving data corpora are being collected. Human transcription of these massive corpora is not only a tedious task, but also subjective and hence prone to errors/inconsistencies which can be due to multiple transcribers as well as lack of enough training/instructions. These human transcription errors can potentially hinder the development of algorithms for advanced safety systems, and lead to performance degradations. In order to prevent these errors from propagating, an automatic maneuver boundary (also activity) detection system (or in short a MAD tool) utilizing filterbank analysis of vehicle dynamic signals is proposed. Using a minimal set of generic vehicle dynamic sensor information, it is shown that the MAD tool can match human transcription to an accuracy of up to 99%. The tool performs equally well on CAN-bus signals as well as inertial sensor information from a portable device. This simple, accurate, and computationally efficient tool can help mitigate human transcription errors and make valuable data from large naturalistic driving corpora more accessible.

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INTRODUCTION

Driving is inherently a complex task requiring the full attention of the driver, both physically and cognitively. Although the driver's skill and experience influence driving, every driver needs to pay attention to changes within and outside the vehicle [1, 2]. With the primary goal of safely arriving at the destination, the driver needs to control and navigate the vehicle through varying traffic and road conditions. Here, active safety systems play a vital role in assisting the driver to accomplish this complicated task by providing and performing adaptive and automatic actions.

In this regard, an active safety system needs to learn the intentions of the driver while driving in order to provide proper and timely assistance. The driver's primary controls are the steering wheel as well as gas and brake pedals. By keeping the vehicle speed and road geometry as reference, the driver varies these parameters in order to control the longitudinal and lateral movements of the vehicle. Signals from these parameters form a subset of information called vehicle dynamics signals. Drivers control and navigate their vehicles by performing maneuvers which are reflected in the captured vehicle dynamics signals. Some of these maneuvers are

directed due to changing road and traffic conditions, while some others are evasive maneuvers which are performed during critical scenarios. Hence, understanding how these maneuvers are performed becomes essential for developing driver assistance and safety systems. It has been established that, similar to speech where phonemes form words, the smallest meaningful unit of a driving pattern is termed as "drivemes"; drivemes form maneuvers, and maneuver sequences form a navigation route [3, 4]. Therefore, analyzing how these drivemes and maneuvers are executed by drivers can provide information on how the driver controls the vehicle and how driving performance varies over time. Tracking these variations can improve the efficiency of active safety systems in not only providing safety to the driver, but also in predicting actions of drivers.

Identifying abrupt variations in vehicle dynamics signals could give an indication of careless and risky driving maneuvers. This approach has been predominantly adopted in present day active safety systems to identify scenarios when the driver might need assistance [5, 6, 7]. These event detection systems provide an insight into the current driving conditions of the driver; however, the temporal information and situations

leading to the sudden events are not captured. This can also be overcome by analyzing drivemes which form a continuum in navigating the vehicle.

Research in maneuver recognition is not new. Previous studies have employed CAN-bus signals in the maneuver identification task and obtained over 90% accuracy [8, 9]. Sensor information from inertial measurement units (accelerometers, gyroscope and magnetometer) have also been utilized for maneuver recognition with similar performances [10, 11]. In the entire analysis of maneuver recognition, driving maneuvers are often manually transcribed. Manual transcription is, however, feasible for small and focused probe studies, and can become a formidable task which is prone to errors when analyzing large driving corpora. One such massive data corpus is the UTDrive driving data corpus [12] which has more than 100 driving sessions. Although every session is along a fixed route, the variability in terms of different maneuvers during the 15-30 minutes of driving session poses a big challenge to the transcribers who strive to maintain consistency between the transcriptions. In other scenarios, when the data is not collected on a pre-set route, (for example, naturalistic free-style data collection using portable devices), the transcription complexity increases even further. Since we evaluate driving performance after the maneuver recognition stage [13], it is important to have a reliable way to detect maneuver boundaries. This motivates the need for an automatic tool which should be able to minimize human transcription errors. Unlike event detection boundaries which rely on abrupt changes in vehicle dynamics, maneuver boundaries are governed by rules. Maneuvers have a preparatory phase, an execution phase, and a recovery phase [14]. For example, in a right turn maneuver, the vehicle generally coasts towards an intersection by reducing vehicle speed. Then the driver prepares the vehicle orientation by varying the steering wheel angle appropriately in accordance with the road geometry, followed by increasing vehicle speed to complete the turn. Finally as the vehicle picks up speed, it is re-orientated to move within a lane by readjusting the steering wheel angle. A similar scenario is observed with stop signs, where the vehicle coasts towards the stop sign and comes to a complete halt. After a brief time of inactivity, the vehicle speed increases, and during this entire duration, as the vehicle orientation does not change, there is no variation in steering wheel angle. Previous analysis on maneuvers has shown that using simple Fourier Transforms and proper classification boundaries, it is possible to distinguish maneuvers with an acceptable precision [15]. To illustrate this, a scatter plot is shown in Figure 1 with steering wheel angle (SWA) and vehicle speed as the two vehicle dynamics signals. It is evident that maneuvers such as Right Turn (RTR), Left Turn (LTR), Right Road Curve (RRC), Left Road Curve (LRC), Right Lane Change (RLC), Left Lane Change (RLC), Straight (STR) and Stop (STP) are easily

separable in this 2-dimensional space. It can also be seen from Figure 1 that all the maneuvers are well clustered and the stop (STP) maneuver has a high variability. This is primarily due to how the driver approaches the stop intersection and the analysis window size.

The variability found in stop maneuvers is a good indication of how drivers perform under free style naturalistic real traffic conditions. This variability is not reflected in simulated setups or controlled driving conditions. Hence, in the recent past, there is a growing interest in “naturalistic” driving data analysis towards active safety systems. Massive naturalistic driving data corpora such as UTDrive, SHRP2, and the 100-car study from VTTI [16, 17] with hundreds of hours of driving data have been collected. Now, there is a need to prune this massive data to have the ability to select only specific driving regions for analysis. It becomes unrealizable to manually transcribe driving events and maneuvers - a task which is highly subjective and susceptible to human transcription errors.

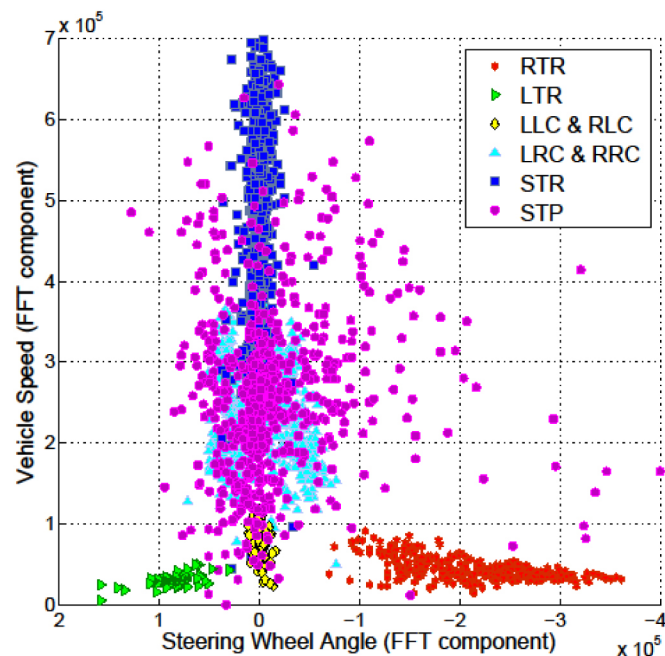


Figure 1. Scatter plot of FFT component of steering wheel angle and vehicle speed showing separability for each maneuver.

The goal of this study is to utilize a minimum set of vehicle dynamics signals towards a computationally efficient, reliable, and fast automatic detection of maneuver boundaries. In addition to vehicle related signals obtained through CAN-bus, sensor information from a smart portable device is also explored for maneuver recognition and analysis. Smart portable devices are gaining importance in naturalistic driving data collection as they are equipped with a variety of useful sensors that can be easily used to instrument vehicles. Hence, it becomes important for the annotation tool to be able to detect

maneuver boundaries in both CAN-bus data as well as inertial measurement signals from the portable device. Using a minimum set of sensor information and appropriate filterbank analysis, variations in the vehicle dynamics are extracted to identify and label maneuver boundaries.

SETUP AND DATA DESCRIPTION

Drivers control the longitudinal and lateral movement of the vehicle by controlling the steering wheel, gas pedal and brake pedal. Therefore, the steering wheel angle and vehicle speed provide a good estimate on the vehicle trajectory. The basic stop maneuver, as depicted in Figure 2, can be easily identified by observing very low longitudinal vehicle movements (i.e., the vehicle speed). However, as it can be observed from the right turn example in Figure 3, the vehicle speed alone is not sufficient as the vehicle slows down even on turns. Other maneuvers are more complex and driving patterns can vary drastically with a change in the vehicle speed at which the maneuver is executed. Steering wheel angle along with the vehicle speed can however provide sufficient information to distinguish these maneuvers. For the sake of consistency and to use a minimum set of sensor information, in this study only the lateral vehicle dynamic variations are considered for identifying maneuver boundaries. Rather than looking at the lateral vehicle acceleration, the steering wheel angle variations are considered for the analysis because they not only contain vehicle trajectory information, but also driver and driving characteristic information which can be utilized for subsequent evaluations. Similar to the vehicle speed, the steering wheel angle can be captured through the CAN-bus. The use of portable devices as data acquisition platform has been previously evaluated and it has been shown that the vehicle yaw (captured from the gyroscope) provides equivalent sensor information as the steering wheel angle [11, 13]. This comparison between different data sources for vehicle steering angle is also shown in Figure 4. These two sensor information are separately analyzed to evaluate and compare performance of the maneuver boundary detection algorithm.

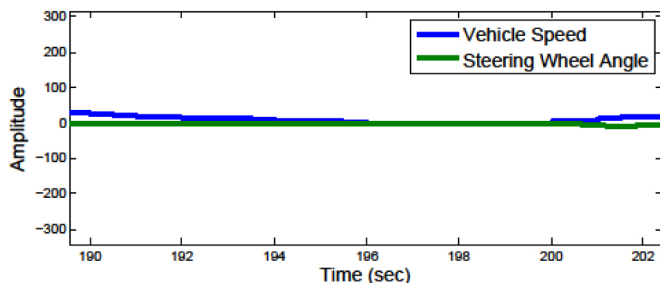


Figure 2. Typical stop maneuver where the vehicle is coasting and not much of a change in the steering wheel angle.

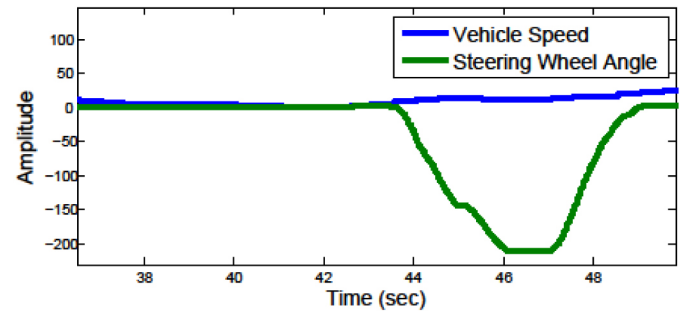


Figure 3. Typical right turn maneuver where the vehicle is coasting and there is a significant change in the steering wheel angle where the driver first prepares, then turns and finally recovers from the turn.

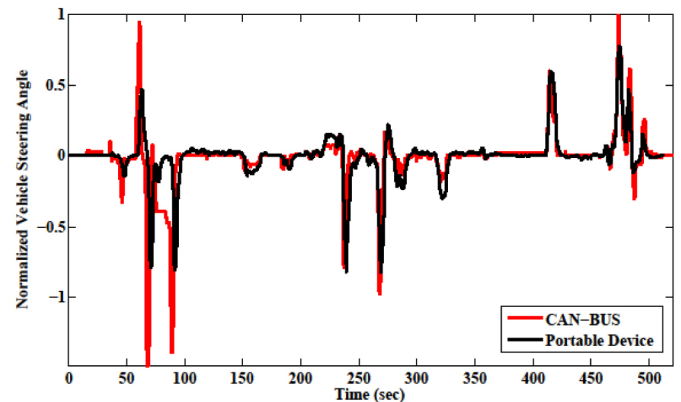


Figure 4. A comparison of steering wheel angle from CAN-Bus and gyro-sensor (yaw) output from portable device.

With over 100 driving sessions of synchronous data collected over a period of 3 years, the UTDive corpus provides a rich database for vehicle dynamic variations under different driving and maneuvering conditions (for a detailed information on the rich multi-modal UTDive and related corpora see [12, 17]). In this study, we utilize a majority of the UTDive corpus (70 driving sessions) which has been transcribed by multiple transcribers for various vehicular activities including different maneuvers. Since we are also interested in developing a generic tool which can be used in automatically transcribing both CAN-bus and portable device signal information, we have also collected a new set of data in the instrumented UTDive vehicle along with the portable data acquisition platform mounted on the windshield as shown in Figure 5. An Android application program (app) was developed to synchronously capture all the available sensor information similar to an instrumented vehicle (for more details on the app and its performance refer to [11, 13]).

The setup shown in Figure 5 enabled us to synchronously capture data in two separate platforms (the instrumented vehicle as well as the portable device). A total of 16 different driving sessions were collected and transcribed for all the maneuvers executed while driving the same pre-defined route and also under no route constraints. The synchronous data which was captured on both platforms were manually transcribed by analyzing the video recordings collected from cameras facing the road.