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Driving Style Recognition Using a Smartphone as a Sensor Platform

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Abstract— **Driving style can characteristically be divided into two categories: "typical" (non-aggressive) and aggressive. Understanding and recognizing driving events that fall into these categories can aid in vehicle safety systems. Potentially-aggressive driving behavior is currently a leading cause of traffic fatalities in the United States. More often than not, drivers are unaware that they commit potentially-aggressive actions daily. To increase awareness and promote driver safety, we are proposing a novel system that uses Dynamic Time Warping (DTW) and smartphone based sensor-fusion (accelerometer, gyroscope, magnetometer, GPS, video) to detect, recognize and record these actions without external processing. Our system differs from past driving pattern recognition research by fusing related inter-axial data from multiple sensors into a single classifier. It also utilizes Euler representation of device attitude (also based on fused data) to aid in classification. All processing is done completely on the smartphone.**

I. INTRODUCTION

In order to promote driver safety, we, among others [1], [2], have found that a driver's behavior is relatively safer when being monitored, when feedback of specific driving events is provided, and when reports of potentially aggressive events are recorded for better understanding. Several companies [3], [4], [5] offer products for fleet management and individual use in order to monitor driving behavior using expensive cameras and equipment, but we believe that we can create a system that is inexpensive, accessible, and intelligently uses the sensors available on a mobile phone. This system will be referred to as MIROAD: A Mobile-Sensor-Platform for Intelligent Recognition Of Aggressive Driving, for the duration of the paper.

In a 2009 study by the American Automobile Association (AAA) Foundation for Traffic Safety, "As many as 56% of deadly crashes between 2003 and 2007 involve one or more unsafe driving behaviors typically associated with aggressive driving" [6]. These actions include excessive speeding, improper following, erratic lane changing and making improper turns. Currently many companies, including the Department of Motor Vehicles (DMV), utilize call service systems with "How am I driving?" bumper stickers on their vehicle fleets to monitor driver safety. These systems claim that drivers who know they are being monitored are less likely to engage in distracted or unsafe driving [2], however, today these systems are ineffective due to the fact that many states prohibit use of cell phones while driving. In order to report an erratic driver, one would need to remember both the number to call and the vehicle ID, or have a passenger report the information. However, as cited by the most recent "Journey to Work" report by the US Census Bureau [7], 76% of workers drive alone, which means that in most cases, a passenger would not be available to report a driver's behavior.

Recently, auto insurance companies such as Progressive [5] have started placing cameras in vehicles to lower insurance rates and monitor driver safety. Similar to vehicle fleet monitoring, insurance companies have also observed that people drive better when being monitored. The systems being deployed in vehicles, such as those created by San Diego-based company DriveCam, have a very high start-up cost. According to an editor at Limousine Charter and Tour Magazine [8], the fleet units are roughly $1000 each, and the company requires a minimum of 20 units to order. The company also charges $30 per month to keep the units online, which makes this an infeasible option for smaller fleets. Family units are also costly, at around $500 per unit with a $30 monthly fee [3].

Driver safety monitoring is not only important for fleet management, but also for monitoring new drivers and assessing performance of drivers during training sessions. Driver safety can be inferred from driver style, which is characteristically classified as either typical (non-aggressive) or aggressive. In order to overcome the high cost of these commercial systems, we have created a novel application for both determining a driver's style (non-aggressive vs. aggressive), as well as recognizing types of driving events using only the sensors on a mobile phone. In contrast to previous research on driving event recognition, our system is implemented completely on a mobile device without using external hardware for processing or review. We can accomplish this by fusing related inter-axial data from multiple sensors into a single classifier based on the Dynamic Time Warping (DTW) algorithm. Using a mobile phone as our sensor platform, the system is both inexpensive and accessible, especially considering the fact that many people already own a device capable of running the application. The system can provide audible feedback if a driver's style becomes aggressive, as well as the information leading up to an aggressive event including video, location, speed and recent driving maneuvers. The system is designed to help prevent incidents by warning a driver if his or her driving style becomes aggressive, and to provide information about incidents so that we have a better understanding of what causes them. If

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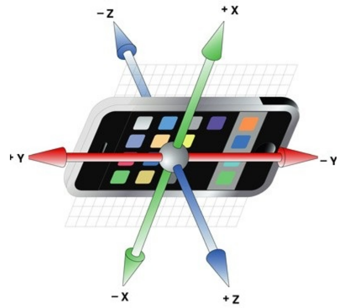

Fig. 1. The axes for accelerometer and gyroscope sensors

widely distributed, anonymous participatory sensing could be used to determine the amount of aggressively-labeled drivers in localized areas. This information could give insight into where incidents are more likely to occur.

Our contributions to this area of research include: a method for determining both driving style and type of driving maneuver, using sensor fusion and the Dynamic Time Warping algorithm; a complete driver monitoring system on a mobile phone that records and plays back video and sensor data in a synchronized manner; and finally a comparison of individual sensors vs. sensor-fused data for driving event recognition using DTW.

This paper is organized as follows. Section II will describe related research in the areas of driving pattern classification and gesture recognition. Section III will outline the system and its features. Section IV will describe the detection and recognition methods used by our system. Section V will show evaluation of the system, and we will conclude with section VI.

II. Related Work

Determining driving style has more importance in the field of driver safety than driver monitoring and reporting alone; it can also be used to assist in holistic sensing for intelligent Driver Assistance Systems (DAS). The Laboratory for Intelligent and Safe Automobiles (LISA) has conducted many research experiments focusing on a driver's style [9], behavior and intentions [10], [11], [12], [13], [14], and their correlation with driver predictability and responsiveness in various driving situations [15], [16]. Driving style has impact on both the predictability of the driver in certain situations, as well as their compliance with feedback from a DAS. MIROAD's ability to detect the driver's style can ultimately aid DASs and increase driver safety.

Two categories of research were reviewed for this project: driving event recognition and gesture recognition. Driving event recognition is critical, because it is exactly the type of research that is relevant to this project. Gesture recognition is closely related and has been researched extensively in recent years due to the widespread availability of accelerometers in devices such as the WiiMote and mobile phones.

A. Driving Event Recognition

In the 2005 paper by D. Mitrović [17], the experimental system included two single-axis accelerometers, two single-axis gyroscopes and a GPS unit (for velocity) attached to a PC for processing. While the system included gyroscopes for inertial measurements, they were not used in the project. Hidden Markov Models (HMM) were trained and used only on the acceleration data for recognition of simple driving patterns. Since the system used HMM, Mitrović had to manually mark hundreds of events for training, which is time consuming and inefficient.

Dai et al. used accelerometer data from a mobile phone to detect drunk driving patterns through windowing and variation thresholding in [18]. In a static position, the false positive rate was very low, but the set of "drunk driving" cues were limited and hard to distinguish from normal driving patterns (for example, weaving and lane changing have the same signature).

A Driver Monitor System was created in [19] to monitor the driving patterns of the elderly. This system involved three cameras, a two-axis accelerometer and a GPS receiver attached to a PC. The authors collected large volumes of data for 647 drivers. The system had many components, one of them being detection of erratic driving using accelerometers. Braking and acceleration patterns were detected, as well as high speed turns via thresholding. Additionally, the data could be used to determine the driving environment (freeway vs. city) based on acceleration patterns. This system, both large and costly ($2735), was used mainly for data recording and offline analysis over extended periods of time.

B. Gesture Recognition

In recent years, many papers have surfaced involving gesture recognition using accelerometers [20], [21]. Devices such as the WiiMote are able to provide raw sensor data to PCs wirelessly, making them advantageous to research. The gesture libraries are typically small and include symbols such as shapes, letters, numbers and application-specific movements such as moving the device up or down quickly to raise or lower the volume on a television. We understand that vehicles have a very limited range of movement and that small gesture libraries and simple algorithms such as DTW are sufficient for our recognition needs. Labeling large numbers of samples for training, for example when using Hidden Markov Models, is unnecessary for the limited set of movements. We will briefly describe the research in this area.

The uWave paper [22] and the gesture control work of Kela et al. [23] explore gesture recognition using DTW and HMM algorithms respectively. They both used the same set of eight simple gestures which included up, down, left, right, two opposing direction circles, square, and slanted 90 degree angle movements for their final accuracy reporting. Four of these eight gestures are one-dimensional in nature. The results proved that using DTW with one training sample was just as effective as HMMs.

Fig. 2. MIROAD in mounted position

We believe that DTW can assist our detection of potentially aggressive events and we can increase accuracy by fusing data from multiple sensors. DTW is suitable for this type of vehicle movement recognition, because the events will vary in length. We also use a more intuitive set of signals for recognition, which decreases confusion of similar driving movements.

III. MIROAD SYSTEM DESCRIPTION (HIGH-LEVEL)

The latest mobile phones are equipped with many useful inputs for research, including, but not limited to:

- Camera (often multiple)
- Microphone (often multiple)
- 3-axis Accelerometer
- 3-axis Gyroscope
- Proximity
- Ambient Light
- Touch
- Magnetometer (compass)
- GPS

These devices are powerful, inexpensive and versatile research platforms that make instrumenting a vehicle for data collection accessible to the general public as well as academia. For the MIROAD system, our focus will be with the rear-facing camera, accelerometer, gyroscope and GPS (for event location and speed only). For device motion, the axes of the phone are set up as shown in Fig. 1. With the mounting arm, we have kept the device rotated on its side and flush with the vehicle dashboard to prevent it from moving, and to ensuring the camera is unobstructed.

A. Sensors and Movement

In the past, most driving pattern recognition systems have used data from accelerometers only. We have decided to use the sensor-fusion output of accelerometer, gyroscope and magnetometer (compass) sensors to detect and classify vehicle movement. The gyroscope signals are a clearer indication of vehicle turn movement, given that they measure rotation rate, and by using the accelerometer and magnetometer in conjunction with the gyroscope, we can get a more accurate reading of device attitude (orientation). The gyroscope measures rotation about itself, while the accelerometer adds correction with respect to gravity, and the magnetometer adds correction with respect to magnetic north. This allows us to more accurately find the Euler rotation (yaw, pitch, roll) from a reference attitude. The detection can be divided into two categories: lateral (turning) T and longitudinal L movements. These categories contain device gyroscope values $G = \{g_x, g_y, g_z\}$ in rad/s, device accelerometer values $A = \{a_x, a_y, a_z\}$ in m/s^2, and device Euler angle rotation $E = \{e_x, e_y, e_z\}$ in radians from a reference attitude R.

$$T = \{g_x, a_y, e_x\} \quad (1)$$

$$L = \{g_y, a_z\} \quad (2)$$

We chose to detect L separately, since it is simpler to threshold the z-axis accelerometer value independently for determining braking and acceleration. While in our project we use g_x, a_y and e_x to classify turning with DTW, we will also examine the accuracy of using pure gyroscope G and pure accelerometer A data in the DTW algorithm. We believe that the set $T = \{g_x, a_y, e_x\}$ is the best choice of signals for distinguishing events with similar movements, and we will show this in our evaluation.

The types of events detected by MIROAD are:

- Right turns (90°)
- Left turns (90°)
- U-turns (180°)
- Aggressive right turns (90°)
- Aggressive left turns (90°)
- Aggressive U-turns (180°)
- Aggressive acceleration
- Aggressive braking
- Swerve right (aggressive lane change)
- Serve left (aggressive lane change)
- Device removal
- Excessive speed

Standard lane changes (non-aggressive) are not currently being detected, because the natural lane change movements observed in our experiments do not exert enough force or rotation on the device to distinguish from noise. The DTW algorithm we are using will only recognize normal and aggressive turn events. Device removal, excessive speed (with respect to the state highway maximum) and braking/acceleration events are easy to detect using thresholds, and will not be the focus of our report.

B. Device Implementation

For this project, we used the iPhone 4 as it contains both an accelerometer and gyroscope. This is integral because we will be using fusion of both sensors for more accurate recognition.

The MIROAD system is mounted in the center of a vehicle windshield as shown in Fig. 2 with the rear-camera facing forward, the device flush with the dashboard, and a car-adapter attached for power (since continuous sensor monitoring quickly drains the battery). Accelerometer, gyroscope and attitude data is sampled at a rate of 25 Hz (to allow slack for processing), while the GPS data is sampled at 1 Hz. GPS is used only to determine speed and where events occur, not as part of the detection or recognition of aggressive movements, due to the fact that GPS is not always available. When the MIROAD application is started, it can be in one of two modes: active or passive.

C. Active Mode

In active mode, MIROAD monitors driving events and does not keep record of any sensor or video data unless a potentially-aggressive event is detected. The system records all data in five minute segments, and deletes them immediately if not flagged. If a potentially-aggressive maneuver is detected, the application will flag the current segment of video and sensor data as record of the incident. This minimizes disk usage to reflect only significant events. The application can optionally send an alert to an external system, via the 3G internet connection, which records the location of the vehicle and type of event. MIROAD is meant to increase the safety of driving, so alerts are audible via a software speech synthesizer. It also detects removal of the system from its mount while in motion, by detecting the force of gravity F_g along each axis. If F_g is completely in the direction of the y or z axis, it is considered a dangerous event. Driver aggression can be determined by the number of potentially-aggressive events over an arbitrary epoch of driving time.

D. Passive Mode

In passive mode, the system records and stores all data for further analysis. The data consists of video and an archive of the raw device motion (acceleration, rotation, attitude, timestamps) with GPS data (longitude, latitude, speed, altitude, timestamps). The data is broken up into five minute segments, just as in active mode. We have also developed an application to playback the synchronized video and sensor data directly on the device for later review. This provides the ability to change filters or recognition algorithms on-the-fly and view the results at a later time.

E. Vehicle vs. Device Motion

In order to assert that the motion seen by MIROAD is identical to the motion of the vehicle, we compared the lateral acceleration seen by the device to that from a vehicle Controller-area Network (CAN) bus. Fig. 3 shows the lateral acceleration readings from both the iPhone 4 and the vehicle CAN bus. The 25Hz iPhone signal was low-pass filtered with a cutoff frequency of 1Hz and the plot was scaled to line up with the 30Hz signal from the vehicle CAN bus. The raw data from the iPhone contains significant amounts of noise from the vibrations of the vehicle interior, but after filtering, the features prove to be highly correlated with a DTW normalized distance between the two signals of $9.2502x10^{-4}$. For comparison, the DTW normalized distance between the CAN signal and zero-mean, unit-variance Gaussian noise is 0.5647.

This concludes the high-level system overview. In the next section, we will discuss the detection and recognition methods in more detail.

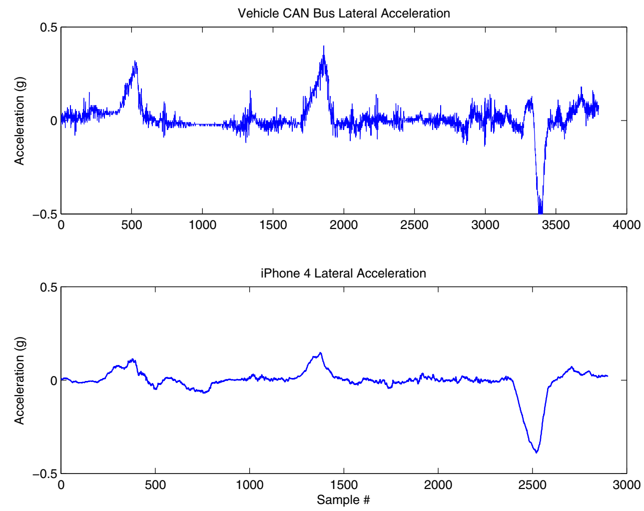

Fig. 3. A comparison of the lateral acceleration output from both the iPhone 4 and the vehicle CAN bus of the 2008 VW Passat sampled at 23 and 30 samples per second respectively (iPhone sample rate varies due to the fact that it is not a real-time system). The raw iPhone 4 signal is very noisy due to vehicle interior vibration so we have used a low pass filter with a 1HZ cutoff. The actual noise from the vehicle is very difficult to determine because it varies depending on both the road conditions and the speed of the vehicle. The DTW normalized distance between the two signals is $9.2502x10^{-4}$. For comparison, the DTW normalized distance between the CAN signal and zero-mean, unit-variance Gaussian noise is 0.5647.

IV. DETECTION AND RECOGNITION ALGORITHMS

In this project, we use the classical DTW algorithm on the three sets of signals mentioned earlier: A, G and T. Using endpoint detection on the live sensor data, we obtained individual events to then process using the algorithm.

A. Endpoint Detection

The MIROAD system collects the motion data from the the accelerometer and gyroscope continuously at a rate of 25Hz in order to detect specific maneuvers. The maneuvers of interest are hard left and right turns, swerves, and sudden braking and acceleration patterns. These maneuvers indicate potentially-aggressive driving that would cause danger to both pedestrians and other drivers. Before we can detect these aggressive driving patterns, we first determine when a maneuver starts and ends using endpoint detection. Once we have a signal representing a maneuver, we compare it to stored maneuvers (templates) to determine whether or not it matches an aggressive event.

In order to detect when events began, we used a simple moving average (SMA) of the rotational energy about the x-axis for a window of size k from the current sample i.

$$SMA = \frac{g_x(i)^2 + g_x(i-1)^2 + ... + g_x(i-k-1)^2}{k} \quad (3)$$

If SMA is greater than an upper threshold t_U then $g_x(i-k-1)$ is the beginning of the event, and the subsequent values of g_x are concatenated until SMA is less than a lower threshold t_L. If the length of the event exceeds 15 seconds, the event is

TABLE I

AVERAGE PEAK LATERAL ACCELERATION

	Left, Right Turns	U-Turns	Swerving
Non-Aggressive	0.30g	0.56g	N/A
Aggressive	0.73g	0.91g	0.74g

discarded. We chose the SMA of g_x, because rotation stands out more than acceleration in all of our recorded events.

1) Maneuver Classification: The DTW algorithm was originally designed as a speech recognition technique by Sakoe and Chiba [24]. Section II described some of the more recent applications of this algorithm with hand gesture recognition, and here we extend it to driving event recognition. The algorithm is summarized below.

Consider two vectors: $X = \{x_1, x_2, ..., x_i, ..., x_m\}$ and $Y = \{y_1, y_2, ..., y_j, ..., y_n\}$ on the left and bottom sides of an m x n grid respectively. Each cell in the grid represents the euclidean distance between each point in the signal:

$$D(i, j) = ||x_i - y_j|| \tag{4}$$

The DTW algorithm is designed to find an optimal alignment of two signal vectors. In our case, we aligned the currently detected event signal with the pre-recorded template signals. For each alignment there exists an optimal warping path p, consisting of the minimum distances between points using a distance function $D(i, j)$. The sum of these distances along the warping path p describes the total cost c_p of the alignment path:

$$c_p(X, Y) := \sum_{k=1}^{K} c(x_{mk}, y_{nk}) \tag{5}$$

The template with the lowest warping path cost is the closest match.

We created five templates for each type of event from all three sensor sets, totaling 40 recording maneuvers and 120 templates. We used the K-Nearest Neighbors (k-NN) classification method with k = 3 to determine the type of event. The five templates were developed using a single vehicle and driver. Templates are recorded using the same endpoint detection technique described above. For each recorded event, three templates are saved simultaneously for the A, G and T sets of signals for accurate comparison. The standard driving events were taken from city driving, while the aggressive driving events were taken in a controlled environment for safety.

When trying to determine whether or not a driving event is typical (non-aggressive) or aggressive, the DTW algorithm finds the closest match between the different styles of templates. The aggressive templates consisted of high-jerk movements and turns that caused loss of traction. On average, these templates had higher peak lateral acceleration values as shown in Table I.

In the next section, we will describe the experimental setup and show our evaluation of the MIROAD system.

TABLE II

MANEUVER RECOGNITION RATE (%) USING A SIGNALS

	Detected Maneuver							
	R	L	U	HR	HL	HU	SR	SL
R	72	0	0	8	0	0	10	10
L	1	68	13	0	1	0	4	13
U	0	46	23	0	8	23	0	0
HR	29	0	0	71	0	0	0	0
HL	0	0	0	0	100	0	0	0
HU	0	0	0	0	0	100	0	0
SR	0	0	0	0	0	0	100	0
SL	0	17	0	0	0	0	0	83

TABLE III

MANEUVER RECOGNITION RATE (%) USING G SIGNALS

	Detected Maneuver							
	R	L	U	HR	HL	HU	SR	SL
R	76	0	0	19	1	0	3	1
L	0	63	3	0	27	0	0	7
U	0	0	46	0	31	23	0	0
HR	29	0	0	71	0	0	0	0
HL	0	0	0	0	100	0	0	0
HU	0	0	0	0	0	100	0	0
SR	0	0	0	0	0	0	100	0
SL	0	17	0	0	0	0	0	83

V. EXPERIMENTAL SETUP AND EVALUATION

The MIROAD system is a completely mobile unit, available for use in any enclosed vehicle. This enables users to bring their driving profile with them wherever they go. Standard vehicle sensors are not available to the general public, and are only able to profile potentially-aggressive maneuvers by vehicle, not by an individual person. Since the MIROAD system can collect the same vehicle movement sensor data as the CAN bus, instrumenting a vehicle to monitor driving patterns becomes much more feasible. In fact, it could be done by anyone owning a new iPhone or Android device.

We have used the MIROAD system in three different vehicles, with three different drivers, and collected over 200 driver events in urban, rural and highway environments. The types of vehicles used were:

- 1992 Pontiac Firebird (Sport)
- 2001 Ford Escape (SUV)
- 2008 Volkswagen Passat (Sedan - instrumented)

The templates for each driving event were recorded by a single driver, in a single vehicle. The A, G and T signal set templates were recorded simultaneously, so there is no bias in their comparison. The comparisons are all made on 1Hz low-pass filtered data using the exact same classic DTW algorithm.

Fig. 4 shows an example of left turn and U-turn templates recorded for signal sets A, G and T respectively. As you can see, the signals are very similar in nature and hard to distinguish from each other. The pitch value (e_x) of the signal set T makes a more clear separation between the 90° left turn and the 180° U-turn.

TABLE IV

MANEUVER RECOGNITION RATE (%) USING T SIGNALS

Detected Maneuver								
	R	L	U	HR	HL	HU	SR	SL
R	92	0	0	6	0	0	1	1
L	0	83	0	0	11	0	0	6
U	0	23	77	0	0	0	0	0
HR	0	0	0	100	0	0	0	0
HL	0	0	0	0	100	0	0	0
HU	0	0	0	0	0	100	0	0
SR	0	0	0	0	0	0	100	0
SL	0	17	0	0	0	0	0	83

TABLE V

RECOGNITION RATE (%) COMPARISON FOR A, G AND T SIGNALS

Detection Rate									
	R	L	U	HR	HL	HU	SR	SL	Total
A	72	68	23	71	100	100	100	83	77
G	76	63	46	71	100	100	100	83	79
T	92	83	77	100	100	100	100	83	91

For our experiments, we collected a set of 201 driving events, of which approximately 50 were considered potentially-aggressive, which were intentional in order to mark them for comparison with the DTW algorithm. The confusion matrices in Table II, Table III and Table IV show true labels (left) compared with classifier labels (top). Maneuvers are labeled right (R), left (L), U-turn (U), hard right (HR), hard left (HL), hard U-Turn (HU), swerve right (SR) and swerve left (SL). Table V shows the total recognition rate for each set of signals. For this specific data set, we had a small amount of false positives for swerve left (SL) maneuvers. These false positives made up roughly 5% of the detected events because of the sharp curvature of the roads near the University of California, San Diego which triggered the endpoint detection. If we raise the energy threshold of the endpoint detector, we can reduce false positives, but we will also reduce the ability to detect short events such as swerving left or right. In order to differentiate aggressive swerving from movements due to road curvature, we would need to add an additional weighting of the lateral force in the endpoint detection.

Our results proved that when using accelerometer or gyroscope data alone with DTW, it is difficult to differentiate a left turn from a U-turn. The U-turn was correctly identified 23% of the time with the accelerometer only, and 46% of the time using the gyroscope. The combined sensor set T used in MIROAD was able to recognize the U-turn 77% of the time. The data also shows that dynamic time warping is a valid algorithm to detect potentially aggressive driving maneuvers. Nearly all (97%) of the aggressive events were correctly identified using the sensor set T, proving MIROAD is a viable sytem for driver style recognition.

VI. CONCLUDING REMARKS

The MIROAD system is a completely mobile, effective and inexpensive way to detect and recognize driving events and driving style. We conclude that the combination of x-axis rotation rate, y-axis acceleration and pitch are the signals best suited for use with the classical DTW algorithm. Additionally, the DTW algorithm can accurately detect events with a very limited training set (templates). MIROAD serves as a novel research tool that can be easily and inexpensively distributed to a wide audience due to the ubiquitous nature of smartphones. The system actively detects and records events that characterize a driver's style, thereby increasing the awareness of potentially-aggressive actions, and further promoting driver safety. Our research shows that the sensors available in smartphones can detect movement with similar quality to a vehicle CAN bus, and therefore make it a viable and inexpensive utility for vehicle instrumentation.

As research advances in the area of holistic sensing for driver safety and assistance systems, we will continue to see a growing fusion of technologies including omni-directional video processing [25], [26], speech recognition [13], driver behavior analysis [10], [11], [12], and object detection [27], [28]. We believe the smartphone platform is a valuable addition to a holistic DAS, not only because of its advanced sensors and ability to recognize driving style, but also because of its access to global networks via its always-on internet connection.

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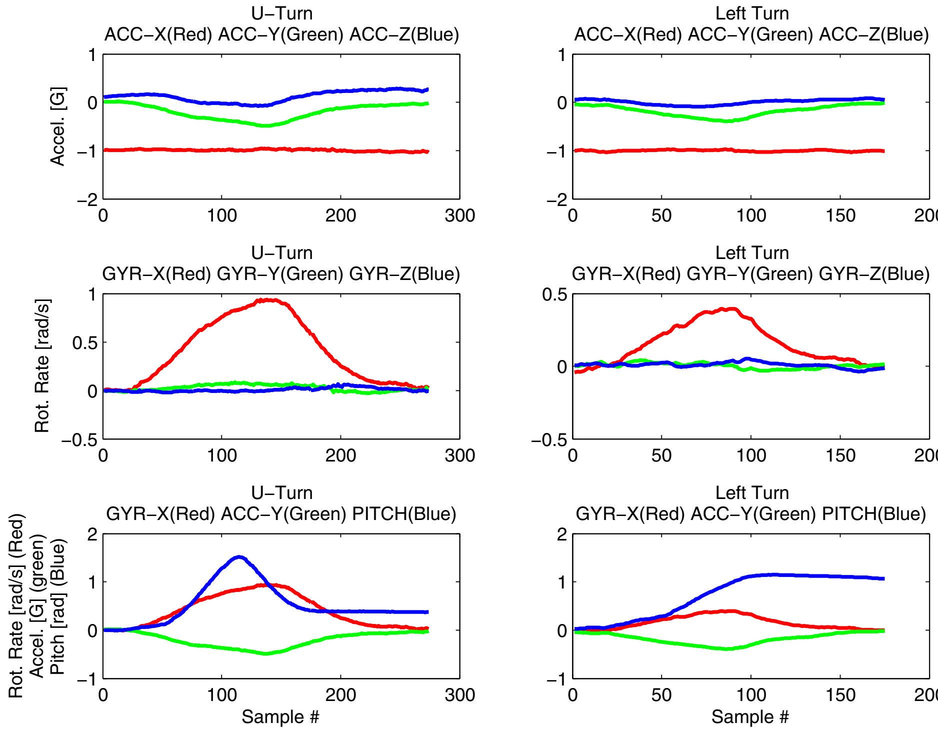

Fig. 4. The left column of graphs represent sensor signals from the same U-turn maneuver and right column graphs represent sensor signals from the same left turn maneuver. As you can see, with accelerometer or gyroscope data alone (rows 1 and 2 respectively), it is difficult to distinguish the U-turn from the left turn. Also, certain axes do not give useful information for driving event recognition. In our experiments, we have used a fusion of rotation rate around x-axis, acceleration on the y-axis, and device pitch (row 3) to better differentiate driving maneuvers using the DTW algorithm.

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