Comparison of GPS and MEMS Support for Smartphone-Based Driver Behavior Monitoring

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***Abstract*—Smartphone-based driver monitoring and other forms of smartphone-based telematics are fast becoming a prevalent trend, especially in the vehicle insurance industry. Choosing the most appropriate sensor system is a pivotal aspect of any driver behavior monitoring system. This paper evaluates the performance of the two sensor systems for smartphone-based driver behavior monitoring and telematics– GPS and MEMS – in terms of the usefulness of data that can be collected for detecting and classifying driving maneuvers as well as the convenience of use and the effect on battery life. Comparisons are done in terms of selected Figures of Merit (FoM) that are commonly employed as metrics for classifying driving style. The results of comprehensive testing show that the MEMS inertial sensors outperform a GPS platform in terms of sampling rate, battery life and the accuracy with which acceleration, braking, swerving and cornering can be detected.**

I. Introduction

Vehicle Monitoring and Telematics (VMT) is a rapidly growing field of interest, especially in the vehicle insurance industry. In recent years, various studies have been done concerning the migration of VMT from dedicated hardware to smartphone-based platforms [1]–[3]. The results have been promising and smartphone-based VMT (SBVMT) has been employed by various automotive insurance companies [4], [5].

One problem inherent to SBVMT, is the sensing platform being under the user's full control and can only be activated by the user when it is convenient. Various insurance companies entice users to activate the application by providing incentives in the form of discounts on monthly premiums and points systems that "gameify" safe driving [6], [7]. Despite these efforts, users still use their own discretion to weigh the benefit and inconvenience of activating a SBVMT application. It is therefore important to make these applications as convenient, unobtrusive and transparent as possible. Applications that require a fixed orientation within the vehicle, or consume excessive battery power should therefore be avoided, which adds complexity to the application. Further studies show that the accuracy of the information gathered and the concluding feedback to a driver has a notable effect on a user's confidence in a system [8]. This further emphasises the need for an accurate sensing platform.

The options for collecting the information necessary for VMT are essentially limited to GPS and processed data from various Micro-Electromechanical Systems (MEMS) including inertial measurement units (IMU) such as gyroscopes and accelerometers.

A. Contribution

This paper evaluates the performance of the two options for SBVMT – GPS and MEMS – in terms of the usefulness of data that can be collected for detecting and classifying driving maneuvers (with specific relevance to reckless driving detection) as well as the convenience of use and the effect on battery life. A novel combination of methods for using MEMS to estimate the Figures of Merit (FoM) suggested by Händel et al. are proposed and compared to GPS-based methods performing the same estimations [8].

The rest of this paper is organized as follows: Section II provides an overview of the literature and state of the art concerning SBVMT, including a summary of the methods used, the pros and cons of the two sensor types and a review of the best practices to be observed when using MEMS sensors in this field. Section III describes the testing platform, test scenarios and the specific parameters that will be qualitatively compared. Section III outlines the results of the tests done and section V provides the concluding remarks and plans regarding future work.

II. State of the art

Modern smartphones, despite their widely varying features, typically share a set of standard characteristics that make them particularly useful for driver and vehicle monitoring. They are battery powered, ubiquitous, permanently connectible to the Internet, allow effortless acquisition and installation of software through "app stores" and provide a platform to acquire GPS and other sensor data. In recent years, the advent of compact and energy efficient MEMS has paved the way for smartphones to be equipped with an increasingly diverse, accurate and efficient array of sensors for sensing rotation, acceleration, magnetic field strength, barometric pressure, etc [9]. These sensors have given smartphones the ability to infer large amounts of information concerning their immediate and non-immediate environments.

The Android operating system further facilitates the exploitation of this data by utilizing proprietary algorithms that provide "virtual"- or "synthetic"sensors. These sensors include

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

Reference	Detection technique	Sensors used
Mohan [1]	pattern matching, orientation calibration	accelerometer, microphone, GPS
Dai [12]	pattern matching, orientation calibration	accelerometer, gyroscope
Johnson [13]	endpoint detection, dynamic time warping	accelerometer, gyroscope, magnetometer, GPS
Eren [14]	endpoint detection, dynamic time warping, Bayesian classifier	accelerometer, gyroscope, magnetometer
Fazeen [15]	pattern recognition	accelerometer, GPS
White [16]	pattern matching	accelerometer, microphone, GPS
Wahlström [3]	theoretical tire slip threshold detection	GPS
Händel [8]	multiple figures of merit, threshold detection	GPS
Castignani [2]	fuzzy logic	GPS, accelerometer, magnetometer, weather, time of day

(From Android version 2.3 onward): the "Linear Acceleration" sensor, which provides an estimation of the phone's acceleration with the effect of gravity removed and the "Rotation Vector" sensor, which estimates the rotation of the smartphone relative to the Earth's frame of reference, using a combination of the accelerometer, magnetometer and gyroscope. These synthetic sensors have various limitations for proper operation. The Linear Acceleration sensor, for example, does not function reliably when the device's orientation changes and the Rotation Vector sensor is inaccurate when the device is accelerated [10]. Due to their limitations, only the yaw component of the Rotation Vector will be considered in this paper, as it operates independent of the effects of gravity.

As VMT is such a burgeoning field of study, many initial systems already exist and compete for market share. These systems achieve monitoring using a variety of sensors, algorithms and platforms. The smartphone-based platform can be considered the "new kid on the block", providing numerous advantages over other hardware platforms as discussed by Engelbrecht et al. [11]. In this paper, only the relevant smartphone based systems will be considered.

Despite the variety of methods and sensor combinations used by the systems listed in table I, only Dai and Eren et al. attempts a system that detects and characterizes driving events or driver behavior using only inertial sensors [12], [14]. In many cases, a fusion of GPS and Inertial sensor values are used [13], [15]. The use of GPS positioning, however, presents a few significant obstacles that are not experienced when using inertial sensors:

1) The sample rate of un-augmented smartphone-based GPS is at best about 1Hz, which is too slow to detect and classify certain maneuvers accurately, compared to inertial sensors that have update-rates in the order of 100Hz.
2) GPS has a high energy consumption. Due to the slow (50 bps) data throughput of the GPS-system, GPS-antennas are kept active for longer periods than high-speed GSM-antennas. This is contrary to the prevalent objective of reducing smartphone battery drain where high speed communications are used and the antennas and processor are deactivated periodically to reduce energy consumption. [17]. GPSs average power drain while sampling at 1Hz is close to 370mW, while the average power consumption of sampling three MEMS sensors (gyroscope, accelerometer, magnetometer) at 100Hz is closer to 60mW (refer to table IV).
3) Un-augmented GPS readings have inaccuracies. Smartphone-based GPS location data is accurate to around 18m, a figure that can increase during overcast conditions [18]. This considerably reduces the usefulness of GPS-data for characterizing small driving maneuvers.
4) Reception of GPS-signal is often inconsistent. Tunnels, forests, high-buildings and incorrect placement within a vehicle can all cause a GPS-device to lose its locational fix. In contrast, inertial sensors are entirely self-contained.
5) Initial acquisition of locational fix can take up to 12 minutes (cold start, no A-GPS). This time is drastically reduced by Assisted-GPS (A-GPS) technology, but A-GPS requires cellular data, which is not always available and can incur additional data charges. In contrast, MEMS sensors can be sampled on-demand at any time.

The disadvantages of smartphone-based GPS listed in the above list will be verified in section III-B.

A. Best Practices

Owing to the nature of MEMS sensors, there are some best practices to observe when developing a system based on them.

1) Calibration: MEMS accelerometers are not perfect and can be a scale factor off from the acceleration they measure. Gravity provides an excellent baseline ($9.81 m.s^{-2}$) with which to compare the sensor data and to adjust it accordingly. Gravity also provides a significant problem, as it cannot be distinguished from vehicle acceleration. This wreaks havoc with inertial navigation algorithms and generally causes incorrect results. Furthermore, as the smartphone is mobile, its orientation is not necessarily known or fixed within the vehicle. Bruwer et al. details a method for removing gravitational acceleration from a mobile accelerometer within a vehicle and aligning the sensor axes with the vehicle axes using an unscented Kalman filter and quaternion mathematics [19]. This system, however, only supports a once-of calibration of the orientation of the smartphone relative to the vehicle during initialization. As the smartphone can be moved within the vehicle at any time, the system must constantly be monitored for a smartphone movement within the vehicle. This can be done using the MEMS gyroscope, as the rotation rate of a phone being moved by a person within a vehicle is considerably higher than what can be experienced

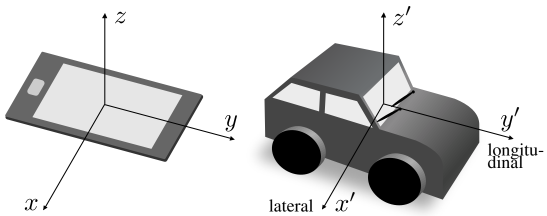

Fig. 1. Smartphone and vehicle coordinate system.

by the vehicle itself.
For the sake of simplicity during comparisons in this paper, the smartphone is fixed and aligned with the vehicle axes as shown in figure 1.

Raw MEMS data recorded within a vehicle is often noisy due to a combination of engine and road vibrations. Engine vibrations occur at around 14Hz, and road vibration can be anything from 10 to 100Hz. Vehicle maneuvers are typically much lower frequency, since their durations tend to be in the order of seconds. It can therefore be useful to apply a low pass filter (LPF) to accelerometer and gyroscope data to remove the bulk of the noise. Furthermore, because Android is not a real time operating system, sensor sampling often does not have the highest priority in the scheduling system, which leads to varying sampling frequencies. All data collected must thus in some way be synchronised with respect to their sample timestamps to avoid drift.

III. Experimental Setup

In this section, the testing platform and proposed tests are discussed in detail.

A. Testing Platform:

A smartphone based logging application was developed to record and store the test data. The application was developed for the Android operating system (API 18 or newer). The application allows the simultaneous logging of any combination of the following sensors to the host-phone's memory card:
Raw MEMS sensors:

- Accelerometer
- Gyroscope
- Magnetometer

Synthetic or virtual android sensors:

- Linear Acceleration
- Gravity
- Rotation Vector

GPS data:

- Latitude
- Longitude
- Speed
- Heading

Battery information (API 21 or later):

- Instantaneous Current Draw
- Average Current Draw

TABLE II
Sensor data received from Android API.

MEMS Sensors			
Accelerometer: ($m.s^{-2}$)	Lateral acceleration (a_x)	Longitudinal acceleration (a_y)	Vertical acceleration including gravity (a_z)
Gyroscope: ($Rad.s^{-1}$)	Pitch rate(g_x)	Roll rate (g_y)	Yaw rate(g_z)
Magnetometer: (μT)	x-axis magnetic field strength (m_x)	y-axis magnetic field strength (m_y)	z-axis magnetic field strength (m_z)
Rotation Vector: (Synthetic sensor calculated from MEMS sensor data).			
x-axis Rotation component q_x ($x \times sin(\theta)$)	y-axis Rotation component q_y ($y \times sin(\theta)$)	z-axis Rotation component $q_z(z \times sin(\theta))$	Scalar component $q_w(cos(\theta))$
Global Positioning System			
Speed(v in $m.s^{-1}$)	Heading (h in deg)	Latitude(C_{la} in deg)	Longitude(C_{lo} in deg)

The information returned by the GPS and MEMS sensors respectively are summarized in table II. Note that these descriptions are only applicable if the smartphone is aligned with the vehicle axes as shown in figure 1 and as discussed in II-A.

The post-processing of sensor data was done using the R statistical language. All post-processing was done to emulate the processing of live data on the smartphone. Therefore, only causal filters are applied and data is processed sample by sample.

The Samsung Galaxy S4 smartphone is used as hardware platform.

B. Proposed tests

The usefulness of the data for reckless driving detection is evaluated by recording a predefined set of maneuvers with the smartphone secured in a fixed orientation within the vehicle, so the phone's axes coincide with the vehicle's axes as illustrated in figure 1. The datasets from the GPS and MEMS are compared and evaluated with regards to the amount of - and the accuracy of the information that can be extracted.

To perform this comparison quantitatively, a common set of variables that can be used to detect and characterize maneuvers must be generated by both the GPS and MEMS sensors.

As there are multiple ways of classifying reckless driving, there are also various types of data that can be used to do so. Händel et al. identified a set of 12 Figures of Merit (FoMs) and classified them in terms of observability, event stationarity, actuarial relevance, and driver influence [8]. Observability is defined as the accuracy with which the FoM can be recorded using GPS, stationarity evaluates for how long a time frame the FoM retains its observability, driver influence qualifies to what extent the driver has the ability to change the FoM and actuarial relevance reflects the amount of risk caused by the FoM.

Table III shows the characterization of selected FoMs:

These FoMs in addition to battery drain and sampling rate can serve as basis for a comparison of the two systems. The

TABLE III
CHARACTERIZATION OF FOMS IN INSURANCE TELEMATICS WHEN CALCULATED USING GNSS-DATA. [8]

FoM	**Observability**	**Stationarity**	**Driver-Influence**	**Actuarial Relevance**
Acceleration	Medium	Low	High	Medium
Braking	Medium	Low	Medium	High
Speeding (Absolute)	High	High	High	Medium
Speeding (Relative)	Medium	High	High	High
Swerving	Low	Low	Medium	Low
Cornering	Medium	Medium	High	Medium
Location	High	High	Low	Medium

test setup for each comparison is discussed in the remainder of this section.

1) Battery Drain: To verify the statistics on battery drain, the time it takes for the application to drain a full battery while logging GPS-data, logging MEMS data and idle is recorded. All logging is done at maximum sample rate. The screen is kept on for monitoring purposes. The battery drain (in mA) can then be calculated as shown in equation 1.

$$I_{avg} = \frac{Capacity(mAh)}{DrainTime(h)} \tag{1}$$

2) Sample Rate: Statistics on the sample rate and variance in sample rate of the various sensors are obtained from logged driving data.

3) Acceleration: The acceleration FoM is defined by Händel et al. [8] as: "The number of rapid acceleration events and their harshness."

The positive y-axis value (a_y) of the MEMS-accelerometer's reading indicates longitudinal acceleration. To obtain acceleration from the GPS-data, however, the velocity measurement must be differentiated as shown in equation 2. When this acceleration exceeds a certain threshold it can be counted as a harsh acceleration. The harshness of the acceleration can be quantified by the magnitude of the acceleration.

$$a(t) = \frac{(v(t) - v(t - \Delta t))}{\Delta t} \tag{2}$$

4) Braking: A similar approach to the one used for the acceleration test(III-B3) can be employed here, but the negative y-axis acceleration, $-a_y$ will be used and compared to the differentiated and negated GPS speed.

5) Speeding (absolute): The smartphone-based GPS provides a location which is typically accurate to within about 18 meters [18]. However it also provides a scalar speed accurate to within $2m.s^{-1}$ calculated with the aid of the Doppler shift in received signals [20]. To estimate the speed of the vehicle using inertial sensors, three different methods are used in this paper.

a) Integration: Estimating the speed of a vehicle accelerating or decelerating in a straight line is done by using equation 3.

$$v_{est}(t) = v(t - \Delta t) + a_y(t) \times \Delta t \tag{3}$$

b) Turn speed estimation: When the vehicle is in a turn the speed can be estimated by using the formula in equation 4. Therefore:

$$v_{est}(t) = a_x(t)/g_z(t) \tag{4}$$

If the vertical axis acceleration (a_z) is below a predefined threshold for a number of consecutive samples, indicating a lack of road generated vibrations, the vehicle can be assumed to be stationary ($v_{est} = 0$). The threshold and the number of samples necessary to avoid false positives is determined empirically in Section IV.

c) Road irregularity autocorrelation: A final method for determining speed using inertial sensors requires a single GPS velocity reading per vehicle as calibration method. As demonstrated by the SenSpeed system developed by Hun et al. A vehicle passing over a road irregularity, such as a speed bump or reflective road studs creates a disturbance in the z-axis acceleration for each wheel passing over the irregularity. If the time between these disturbances (Δt_w) is calculated and the Wheel Base (WB) of the vehicle is known, the speed can be calculated using equation 5.

$$v(t) = \frac{WB}{\Delta t_w} \tag{5}$$

The discrete autocorrelation of the z-axis acceleration data can yield the time between disturbances, as the z-axis acceleration signature is similar for both wheels.

The wheelbase can be requested from the user, but this is inconvenient as the wheelbase of their vehicle is not common knowledge for most users. Instead, it is proposed that the system be calibrated by using the GPS speed until a accurate wheelbase length can be estimated using the reverse of equation 5.

If the detection of speeding is deemed a necessity and the accuracy of the speed estimated using the inertial sensors is insufficient, this speed can be used as a trigger, to request a more accurate GPS-based speed when within a certain threshold of the maximum legal speed limit. This threshold can be determined by quantifying the typical accuracy of the inertial speed estimation.

6) Speeding (relative): To determine if a vehicle is speeding, relative to the applicable speed limit in his location. The road on which the vehicle is driving must be identified and an external map database with updated speed limit for the applicable road must be consulted. This typically requires constant and fine GPS positioning.

Another method proposed to determine the local speed limit is a combination of the speed estimation done in section III-B5, a digital speed limit database (an example of a free community-driven one is Wikispeedia [21]) and Geo-fencing.

Geo-fencing is a method of setting a digital perimeter of a specified radius around a specified point and monitoring whether a device is within or outside of the perimeter. This method of providing location awareness is useful as it allows the phone to only use energy consuming GPS-positioning when the accuracy is required, when possible more energy-efficient positioning such as, cellular tower triangulation or WiFi-positioning can be used.

In an embodiment of this method, an application can be designed to, initially, obtain a fine GPS-location fix and query the speed limit database to find the current speed limit and the closest different speed limit. A Geo-fence can now be defined with a radius equal to the distance to the nearest change in speed limit. Once the perimeter is crossed, this process can be repeated, thereby insuring the minimum amount of GPS usage.

The inertial navigation system (INS) discussed in section III-B9 could also be used instead of Andriod's built in Geo-fencing API.The testing of this method is beyond the scope of this paper. The legal aspects of this form of reckless driving detection requires further study and anonymous participation data for testing.

7) Swerving: Swerving is generally defined as "causing to change direction abruptly". To quantify swerving one can record the number of swerves and their harshness. Swerving typically happens when trying to avoid an object in the path of the vehicle, performing abrupt lane changes or making coarse course corrections. These maneuvers are exceedingly important to detect and classify as they are effective indicators of drunk-, fatigued-, distracted- and aggressive driving [12], [13], [22].

Using Inertial sensors, this is easy to identify as a brief spike in either lateral acceleration (a_x) or yaw rate(g_z), the magnitude of the lateral acceleration is an effective indicator of the harshness of the swerve as a higher lateral acceleration equates to a higher probability of the vehicle skidding or rolling.

Identifying a swerve via GPS is more challenging. The yaw rate as shown in equation 6 and the lateral acceleration of equation 7 can be estimated from GPS parameters. As swerving is often a very brief event and the change of direction is typically corrected almost instantly to coincide with the original heading, GPS, due to its 1Hz update rate, will seldom be able to identify a brief swerve event, much less the harshness of it.

$$\tilde{g}_z(t) \approx \frac{(h(t) - h(t-1))}{\Delta t} \tag{6}$$

$$\tilde{a}_x(t) \approx \frac{v(t) \times \sin(h(t) - h(t-1))}{\Delta t} \tag{7}$$

8) Cornering: The definition used for cornering will, in this paper, differ from the one given by Händel et al. Händel et al. describes the cornering FoM as: "The number of events when turning at too high speed and their harshness". As shown by Zeeman et al. and Wahlstr´om et al. [3], [23], the two main dangers of harsh cornering are tire slip and rollover, both of which are indicated by a large lateral acceleration. The definition of harsh cornering for this paper will therefore be defined as: "The number of events when turning above a predefined lateral acceleration threshold and their harshness"

Wahlstr´om et al. [3] proposes a method for extrapolating turn harshness from GPS data. Their method involves a Kalman filter algorithm applied to the parameters of the GPS to continuously update an estimate of the ratio between the normal and horizontal force on the vehicle's tires. This ratio determines the threshold at which the vehicle will slip. Despite the large amount of processing done on the GPS data, the amount of missed detections and false alarms summed to approximately 40% of the total number of cornering events.

As with swerving, cornering events and their harshness can easily be deduced from inertial sensor readings. An extended increase in lateral acceleration (a_x) and yaw rate (g_z) indicates a cornering event, and the magnitude of the lateral acceleration (a_x) is proportional to the harshness of the cornering event.

9) Location: Location data is useful in a SBVMT system for three reasons. Firstly, certain geographical areas can be flagged for a higher rate of accidents and thereby increasing the risk of driving there, secondly, the location of the vehicle can be useful to transmit for telematics purposes and remote monitoring and finally, the location of an event on a map is a useful way of providing post-driving feedback to a driver.

A simple and computationally efficient inertial navigation algorithm is developed below to obtain the 2-dimensional Cartesian coordinate position, heading and speed of the vehicle from the Accelerometer, Magnetometer and Gyroscope data.

The inertial navigation algorithm proposed here is based on the following basic methods, and the algorithms are deliberately chosen to be as simple as possible for the purpose of computational efficiency. Heading can be estimated by equation 8 and, if the magnetometer has been deemed calibrated, the proprietary Android rotation vector synthetic sensor can be used to calculate the heading.

$$h_{est}(t) = h(t - \Delta t) + g_z(t) \times \Delta t \tag{8}$$

Where h_{est} is the estimated heading and Δt is the sampling period.

$$h_{est}(t) = atan2(2 \times q_y \times q_w - 2 \times q_x \times q_z, 1 - 2 \times q_y^2 - 2 \times q_z^2) \tag{9}$$

To calculate the coordinate position from MEMS sensor data, an initial point must be defined as the start of the event, the origin (0,0) is defined as the starting point. Given the starting coordinate $C(0) = (C_l a(0), C_l o(0)) = (0, 0)$ The next coordinate can be calculated as shown in equations 10 and 11:

$$C_{la(est)}(t) = C_{la(est)}(t - \Delta t) + v_{est}(t) \times \Delta t \times \cos(h_{est}(t)) \tag{10}$$

$$C_{lo(est)}(t) = C_{lo(est)}(t - \Delta t) + v_{est}(t) \times \Delta t \times \sin(h_{est}(t)) \tag{11}$$

The coordinates estimated by equations 10 and 11 are, in contrast to the GPS measurements, in meters, relative to the start of the event and not in decimal degrees relative to the Prime Meridian at the equator.

TABLE IV
RESULTS OF TESTS ON BATTERY DRAIN FOR THREE MEMS SENSORS VERSUS GPS.

	Idle	GPS	MEMS
Drain time (hh:mm:ss)	04:56:25	04:08:39	04:47:26
Current draw (mA)	526	627	542
Relative current draw	-	101.08	16.44

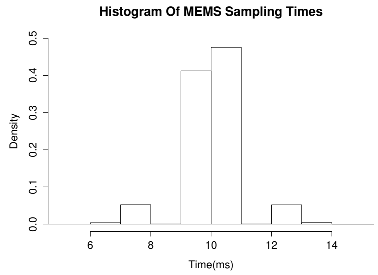

Fig. 2. A histogram of the MEMS-sensors' sampling period.

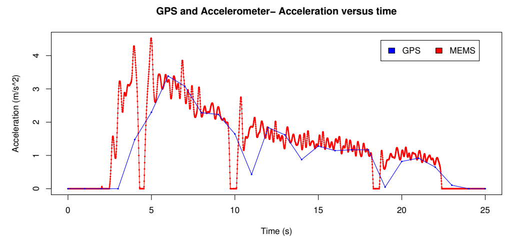

Fig. 3. A plot of the vehicle's acceleration over a 25 second interval.

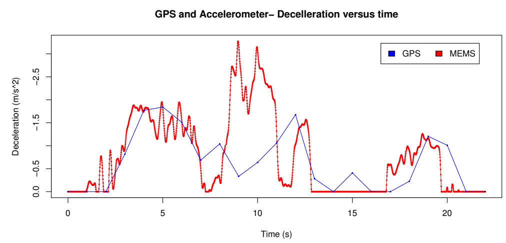

Fig. 4. A plot of the vehicle's deceleration over a 22 second interval.

For the sake of comparison, the initial GPS coordinates $C(0)$ are subtracted from each subsequent GPS coordinate and multiplied by an estimation of the earth's radius at that position ($6370 \times 10^3 m$ at $-33 \deg latitude$), thereby recording the coordinates in meters relative to the origin or C(0).

IV. EXPERIMENTAL RESULTS

In this section, the result of the comparisons between the various aspects of GPS and MEMS systems for SBVMT are shown. Quantitative comparisons are done if possible, otherwise, the methods are compared qualitatively in terms of accuracy.

A. Battery Drain

Table IV summarizes the battery drain test statistics for the Samsung Galaxy S4 with a 2600mAh battery:

The current drawn by GPS is therefore more than 5 times that of the MEMS sensors.

B. Sample Rate

The highest possible sample rate of the GPS is 1Hz ($T_s = 1s$), while the MEMS sensors are around 100Hz ($T_s = 0.01s$). This is a significant advantage for the MEMS sensors. The consistency of the sample rate is also important however, and here the MEMS sensors have a slight variation in sampling period. Figure 2 shows a histogram of the MEMS sampling periods.

The GPS is within 10% of its correct sampling period 99.81% of the time, while the MEMS-sensors are within 10% of their correct sampling period 88.81% of the time.

C. Acceleration

Figure 3 shows the acceleration of the vehicle over a 25 second interval. It is clear that, despite the similarities in acceleration magnitude, the GPS cannot capture the higher frequency acceleration events. The filtered accelerometer data shows the higher peak accelerations, that the 1Hz differentiated GPS-speed fails to detect. From the figure, the gear shifts are also clearly visible at 4, 10 and 18 seconds. The GPS-data also has a delay with respect to the acceleration. Though the error is small over the long term, the detection of sharp accelerations and gear shifts are useful for SBVMT and the MEMS-sensors clearly perform much better.

D. Braking

Figure 4 shows three minor vehicle deceleration events. Similar to the results with acceleration, the GPS cannot record the sharp accelerations as effectively as the MEMS sensors, though the average acceleration over the period is similar for both systems.

E. Speeding(Absolute)

The speed of a GPS is typically accurate to within $2m.s^{-1}$, therefore, in this test, the GPS speed will be used as a benchmark to quantify the accuracy of the speed estimated with MEMS. Figure 5 shows the speed estimated by MEMS sensors via accelerometer integration (III-B5a) and turn speed calculation (III-B5b). This sample has been chosen to illustrate the drift in estimation when there are no fixed reference speeds to work with. The large error in this sample is caused by a variation in road incline, conflicting with the assumption that tests are carried out on a level surface. The slight incline change causes the accelerometer to measure a component of the earth's gravitational acceleration, thereby causing a drift in the speed estimation. The effect of gravity can be mitigated using the methods discussed in II-A. The turn speed estimation was found to be accurate only for turns with a high yaw rate, where the integrated speed can then be corrected. Those corrections are shown in green in figure 5. The other method

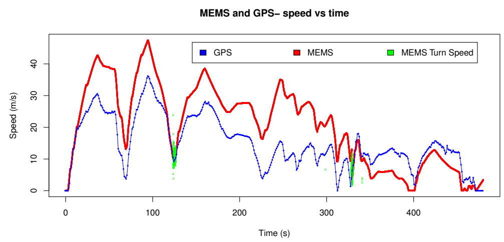

Fig. 5. A plot of the speed of a vehicle, estimated via MEMS integration (Red), MEMS turn speed estimation (Green) and GPS-Speed (Blue)

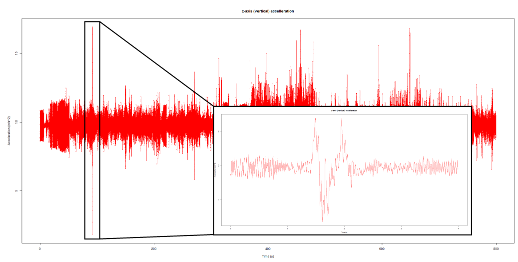

Fig. 6. An extract from a plot of the z-axis (vertical) acceleration measurement versus time. The two impulses in the extract represent the front and rear wheels respectively impacting with a speed bump.

for estimating speed through autocorrelation of the z-axis acceleration was found to perform well at low speeds of up to 40 km/h. Figure 6 shows a sharp z-axis acceleration caused by driving over a speed-bump at 20km/h. The two spikes where the front and rear wheels hit the bump are clearly visible. For this case, the autocorrelation of the extracted data had a local maximum at 490ms. The vehicle in consideration has a wheel base of 2.6m, which in turn gives an estimated speed of 19.1 km/h while the GPS speed at that point in time is 21.38 km/h.

F. Swerving

As shown by figure 7, the MEMS sensors excel at detecting the brief lateral accelerations and rotations associated with swerves. GPS, however lacks the update rate necessary for detecting events shorter than two seconds.

G. Cornering

The lateral acceleration can be recorded directly by the MEMS sensors during cornering as shown in figure 7, avoiding the necessity for calculating lateral acceleration. The implementation of an algorithm for acquiring accurate lateral acceleration data from GPS data is considered beyond the scope of this paper. Suffice it to say that, identifying and rating the harshness of cornering events is significantly easier and more computationally efficient using MEMS than GPS.

H. Location

The comparison of the inertial navigation algorithm with the GPS data showed that, as was expected, integrated noise of the accelerometer and gyroscope measurements led to large errors over time. Furthermore, the assumption that all tests were done on level ground, allowed gravity to cause drift in the speed as discussed in section II-A1. However, for single maneuvers or events, lasting less than a minute, the system did prove accurate at mapping the coordinates as long as the initial velocity was accurate. Figure 8 shows the drift in speed and coordinate position calculated by inertial navigation algorithm.

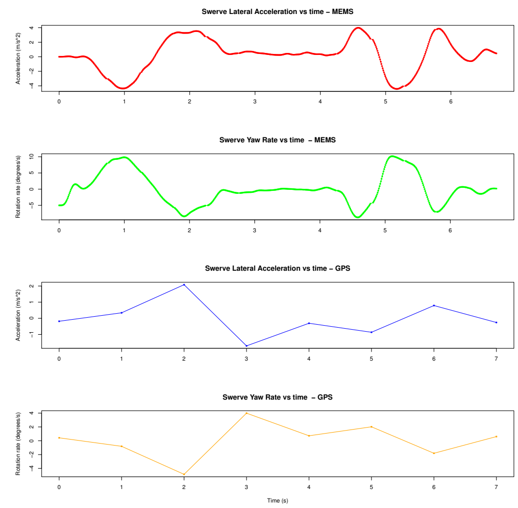

Fig. 7. A series of plots showing the lateral acceleration and yaw rate measured by the MEMS sensors and estimated by the GPS over a 7 second period containing a brief lane change and a swerve around an object, respectively.

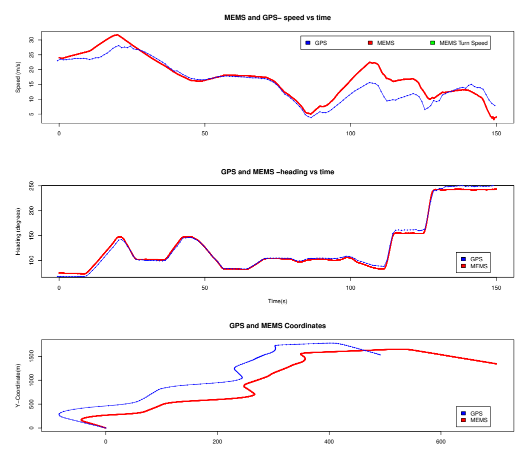

Fig. 8. Three plots comparing the speed, heading and coordinates estimated by the MEMS sensors and measured by the GPS.

V. Conclusions

MEMS technology has enabled smartphone based sensors to grow from strength to strength in recent years and the improvement of their accuracy, efficiency and size show no signs of slowing. The information provided by these sensors are being thoroughly exploited by industries such as fitness,

TABLE V
A SUMMARY OF THE COMPARISON BETWEEN MEMS AND GPS METHODS.

Test:	GPS:	MEMS:
Battery Drain (IV-A)	101.08 mA	16.44 mA
Sample Rate (IV-B)	1 Hz	100 Hz
Acceleration (IV-C)	Misses brief accelerations	✓
Braking (IV-D)	Misses brief decelerations	✓
Speeding (IV-E)	✓	Inaccurate without reference points (turns, bumps)
Swerving (IV-F)	✗	✓
Cornering (IV-G)	Lateral Acceleration requires complex algorithms	✓
Location (IV-H)	✓	Only brief events

gaming and lifestyle. In this paper we considered ways to employ MEMS-sensors instead of GPS in the field of SBVMT. The best practices when using MEMS-sensors were discussed with reference to the current state of the art. The pros and cons of both systems were listed and then verified throughout the rest of the paper. Practical test setups were proposed to thoroughly evaluate and compare both systems in ways they would typically be used to gather data for SBVMT. Table V provides a brief overview of the results of each test. It is clear from these tests, that MEMS-sensors outperform GPS in various aspects of SBVMT including the detection of swerving as well as sudden accelerations and decelerations, but there are other areas where GPS is still indispensable, such as providing locational data. Due to mostly to its lower power consumption and its independence of unreliable external communications it is the view of the author that MEMS-sensors holds the advantage for use in, for example, reckless driving detection systems.

A. Future work

Future work in this area will be focused on acquiring a large and representative set of data for testing purposes. Methods for removing the effect of gravity from readings and distinguishing between vehicle motion and smartphone motion within the vehicle must be perfected. Different techniques for classifying the MEMS data and detecting driving events will be investigated, with the final goal of developing a complete, accurate and convenient smartphone based reckless driving detection system.

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