Vehicle acceleration estimation using smartphone-based sensors

BACKGROUND

One of the prevalent trends in the contemporary mobile industry is the use of the powerful integrated sensors in mobile devices to gather and process information in our everyday lives, a trend which branches from the biggest buzzword in modern electronics: *The Internet of Things*. These sensors have yet to be properly implemented to monitor one of the most perilous parts of our everyday lives, namely commuting. The advent of smartphone-based sensing could provide a simple, inexpensive way to identify and reduce reckless driving.

The accelerometer features prominently in most proposed vehicle monitoring and reckless driving detection systems (Zeeman *et al* 2014; Schietekat *et al* 2013; Engelbrecht *et al* 2014). In vehicle monitoring it is imperative to distinguish between accelerating, decelerating and lateral acceleration, since this data can be used to identify and classify driving manoeuvres and events effectively. Accurate coordinate acceleration data is therefore the main concern of this project.

Accelerometers, however, measure what is known as proper acceleration (the acceleration relative to a free-falling point), not coordinate acceleration (the acceleration relative to a stationary point). The proper acceleration of an object that is stationary with respect to the earth will therefore be 1 G (1 x 9.81 $m.s^{-2}$) upwards in the earth axes.

Within a vehicle monitoring system there are three sets of axes of concern: the earth axes, the vehicle axes and the sensor axes. In a dynamically moving vehicle with a smartphone-based sensor providing measurements, these axes are not necessarily constrained by known or fixed orientations relative to one another. The accelerometer measurement in the sensor axes will therefore be corrupted by the effect of gravity with an unknown orientation.

The effect of gravity can be removed from the proper acceleration reading (in the sensor axes) if the orientation of the sensor axes relative to the earth axes can be found. The coordinate acceleration in the sensor axes can be rotated from the sensor axes to the vehicle axes if the orientation of the sensor relative to the vehicle can be determined, thereby yielding the coordinate acceleration in the vehicle axes.

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AIMS AND OBJECTIVES

The aim of this project is therefore to present a way of quantitatively measuring, recording and displaying the acceleration of a vehicle along its own axes – with the effect of gravity removed – to enable reckless driving detection. This is to be done using only the sensors commonly found in a smartphone (accelerometer, gyroscope and magnetometer).

PROJECT DESCRIPTION

For this project, the use of a smartphone and smartphone-based sensors was emulated by using a sensor hub (gyroscope, accelerometer and magnetometer) connected via USB to a mobile computer running the software-based estimator. The basic operation of the software-based estimator can be summarised as follows:

1. The system is initialised while the vehicle is stationary.
2. As the vehicle accelerates for the first time after start-up, the orientation of the vehicle relative to the sensor is calculated.
3. The orientation of the sensor relative to earth is calculated.
4. The known gravitational acceleration is rotated from the earth axes to the sensor axes.
5. The gravitational acceleration in the sensor axes is then subtracted from the current acceleration measurement in the sensor axes.
6. The resulting gravity-free acceleration is then rotated from the sensor axes to the vehicle axes.

Steps 3 to 6 are repeated to update the acceleration estimation. These steps are discussed in more detail in the sections following.

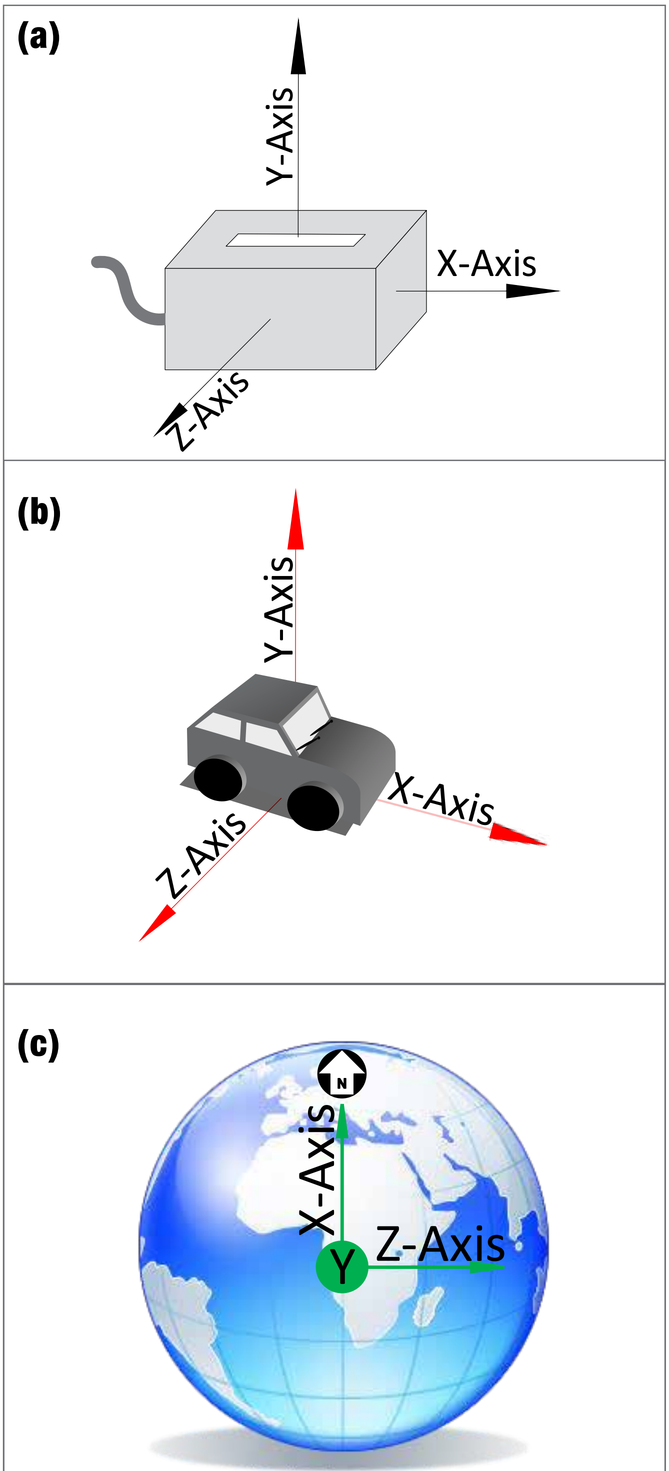

Figure 1: Illustrations showing the conventions for the orientations of (a) the sensor axes, (b) the vehicle axes, and (c) the earth axes

Calibration

The sensors are assumed to be stationary for the first 200 cycles of the program (4–8 seconds, processor dependent). During this time, and continuing until the sensors are detected to be moving (accelerating), a moving average and variance of 200 samples is calculated. The moving average of the acceleration is used as an estimate of the earth's gravity in the sensor axis, while the mean gyroscope reading is used as the constant gyroscope bias and is subtracted from all subsequent gyroscope data. The calibration for the magnetometer is done by subtracting the lowest value encountered from the reading and then dividing by the difference between the highest and the lowest value encountered.

Calculating the orientation of the vehicle relative to the sensor

The calibration of sensors stop and the recording of the first acceleration starts when the device starts moving (accelerating). The transition from stationary to accelerating is, for this project, defined by a sustained difference between acceleration magnitude and the mean of the acceleration up to that time. The first acceleration is recorded and the orientation of the vehicle relative to the sensor is calculated using the direction of the first acceleration in the sensor axes, the direction of gravity in the sensor axes and the assumption that gravity lies in the vehicle's X–Y plane.

The objective is to find the quaternion (a four-dimensional complex mathematical representation of a rotation) describing the rotation from the sensor axes to the vehicle axes. An objective function which can be minimised to find the most accurate quaternion rotation q_S^V is shown in Equation 1.

$$f(q_S^V, d^V, m^S) = q_S^V \otimes d^V \otimes q_S^{*V} - m^S \quad (1)$$

where d^V represents the direction of the front of the vehicle in the vehicle axes and m^S is the normalised measurement of the first acceleration in the sensor axes.

$$d^V = 0 + 1i + 0j + 0k \quad (2)$$

$$m^S = 0 + m_x i + m_y j + m_z k \quad (3)$$

The objective function is minimised by using the gradient descent method.

Calculate the orientation of sensor relative to earth

To avoid local minima with the gradient descent algorithm, an informed guess is made as to the initial orientation of the sensor relative to earth using the estimated direction of gravity.

Initialise Unscented Kalman Filter

An Unscented Kalman Filter (UKF) is used to combine accelerometer, gyroscope, magnetometer and vehicle dynamics data in a way that maximises the probability of a correct estimation of the sensor's orientation relative to the earth axes. The parameters needed to initialise a UKF are:

- Transition function – f
- Observation function – g
- Transition covariance – Q
- Observation covariance – R
- Initial state mean – μ_0
- Initial state covariance – Σ_0

The optimal state vector is chosen as the four-part quaternion orientation with the three-part rotational velocity appended as shown in Equation 4.

$$x_k = [q_1, q_2, q_3, q_4, \omega_1, \omega_2, \omega_3]^T \quad (4)$$

A combination of the two objective functions similar to that in Equation 1 (one for the accelerometer reading and the vertical y-axis and one for the magnetometer reading and magnetic north) is minimised by using the gradient descent method to obtain an estimate of the orientation of the sensor relative to earth.

The four-part quaternion orientation calculated here is combined with the three-part gyroscope reading to provide an observation vector (shown in Equation 5) for the UKF.

$$x_k = [q_{m1}, q_{m2}, q_{m3}, q_{m4}, \omega_{m1}, \omega_{m2}, \omega_{m3}]^T \quad (5)$$

Update Kalman filter

For the first run, the Kalman filter is updated with the same mean and covariance used to initialise the filter, as well as the observation vector defined in Equation 5. For each iteration of the system, the Kalman filter is updated with the mean and co-variance output from the previous Kalman filter iteration, as well as the new observation vector.

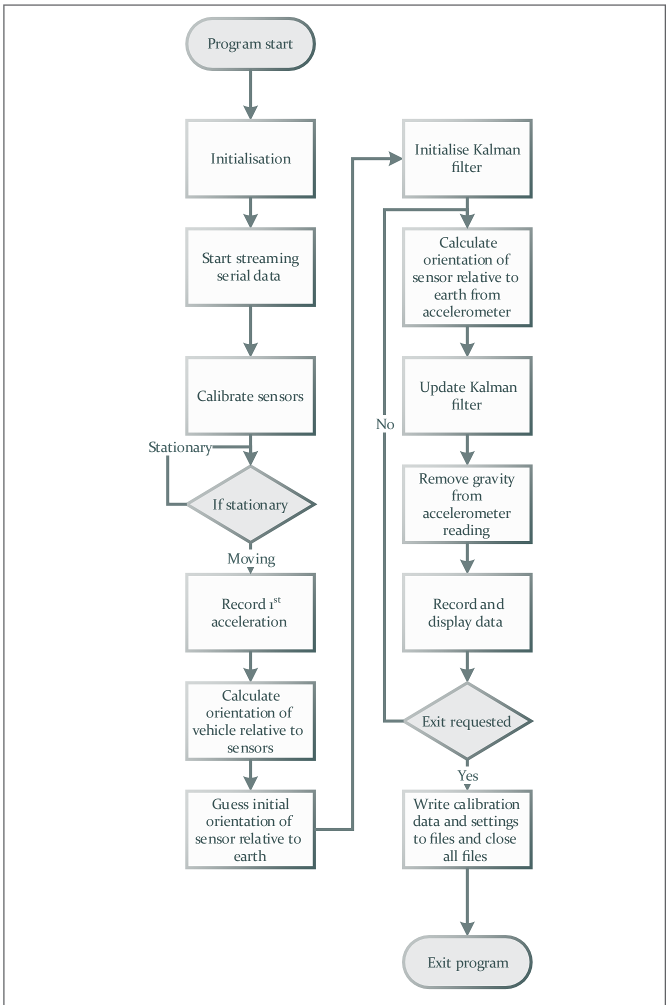

Figure 2: A flowchart illustrating the basic program operation

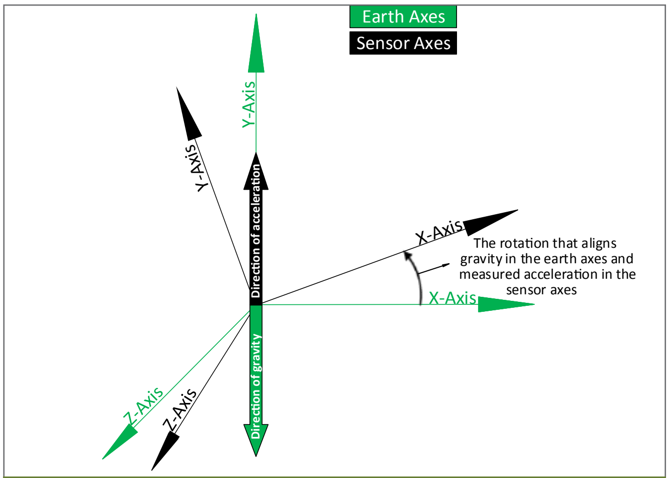

Figure 3: An illustration of the rotation q_E^S and how it is estimated using an accelerometer reading

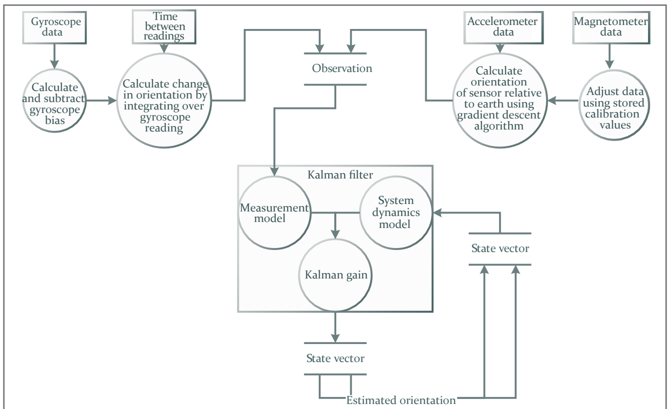

Figure 4: A data flow diagram illustrating the underlying flow of data within the system

Rotate gravity from the earth to the sensor axes

The magnitude of gravity in the earth axes can now be rotated into the sensor axes as shown in Equation 6.

$$g^S = q_E^S \otimes g^E \otimes q_E^S \quad (6)$$

Remove gravity from acceleration measurement

This gravitational acceleration in the sensor axes can now be subtracted from the sensor measurement as shown in Equation 7.

$$\overline{a}^S = a^S - g^S \quad (7)$$

Rotate resultant acceleration to vehicle axes

The resulting acceleration in the sensor axes can now be rotated to the vehicle axes as shown in Equation 8.

$$\overline{a}^V = q_S^V \otimes \overline{a}^S \otimes q_S^V \quad (8)$$

Record and visualise acceleration

The resultant calculated acceleration data is visualised to better facilitate the comprehension of what has been achieved in this project. The data is also recorded to enable the analytical measurement of the accuracy of the results.

The data is displayed using Visual Python. A 3D set of axes that represent the earth's axes are displayed in green, and a red object from which the orientation is easily identifiable represents the vehicle's axes. The orientation of the red object is defined by a combination of the quaternions q_E^V and q_S^V as shown in Equation 9.

$$q_E^V = q_E^S \otimes q_S^V \quad (9)$$

The position of the red object relative to the origin represents the instantaneous acceleration of the vehicle in the vehicle axes. Examples of the 3D model's orientations and positions are shown in Figure 5. The magnitude of the acceleration is also shown by the bars in Figure 6.

TESTING AND RESULTS

The testing of the system proved to be a non-trivial task, as a known acceleration with a constant known sensor orientation is difficult to reproduce. The novel tests in Table 1 were implemented to thoroughly test the system and quantify errors.

As the system is designed to be used in a vehicle, tests were done with the sensor in a secure position in the vehicle. For all tests, the normal calibration procedure is followed where the vehicle remains stationary on a road with a level horizontal gradient for the duration of calibration and is then accelerated forward in order for the system

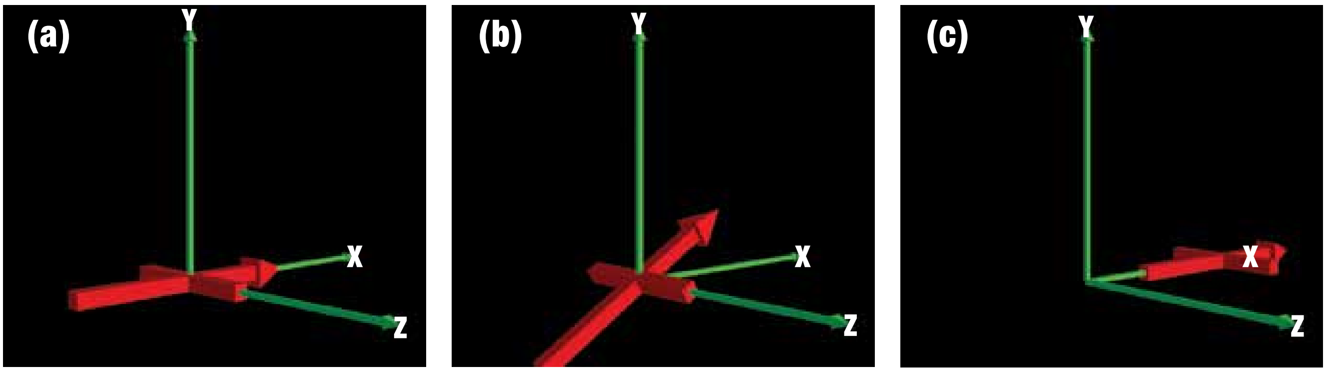

Figure 5: Screen shots showing the position and orientation of the 3D model for situations where the vehicle is (a) not accelerating, (b) on an incline at constant speed, and (c) accelerating on a level road

Table 1: The various tests done and the motivations for doing them

Test	Motivation
Stationary test	Used as a baseline and to quantify sensor noise.
Constant speed and level road test	To quantify the noise contributed by vibrations and road irregularities at different speeds.
Deceleration test, no incline	To compare theoretical average x-axis deceleration over an interval with the average measurement over the interval.
Deceleration test on an incline	To test whether gravitational acceleration influences the measurements and if the vehicle–sensor orientation can be correctly calculated on an incline.
Constant speed and varying incline test	To test if the system can adjust for sudden changes in incline.
Constant speed and turn radius test	To test for accurate lateral acceleration data.

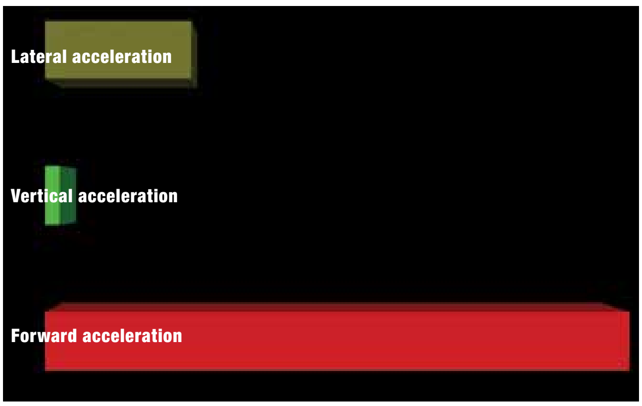

Figure 6: A screen shot of the acceleration bars displayed by the program. The size of the bar increases with the magnitude of acceleration in each axis. The colours of the bars also vary from green for small acceleration magnitudes, to red for large acceleration magnitudes

to determine the orientation of the sensor relative to the vehicle. All speeds are measured and saved programmatically with a GPS.

Summary of results

Comprehensive vehicle testing of the final system was done and the measured results were compared to theoretically calculated results. All results were accurate and promising, except for the sustained lateral acceleration test.

The minimal acceleration error in the vehicle's x-axis and z-axis during constant speeds shows that acceleration events of 30 mG or more are detectable by the system. This opens doors for, not only reckless driving detection, but applications where

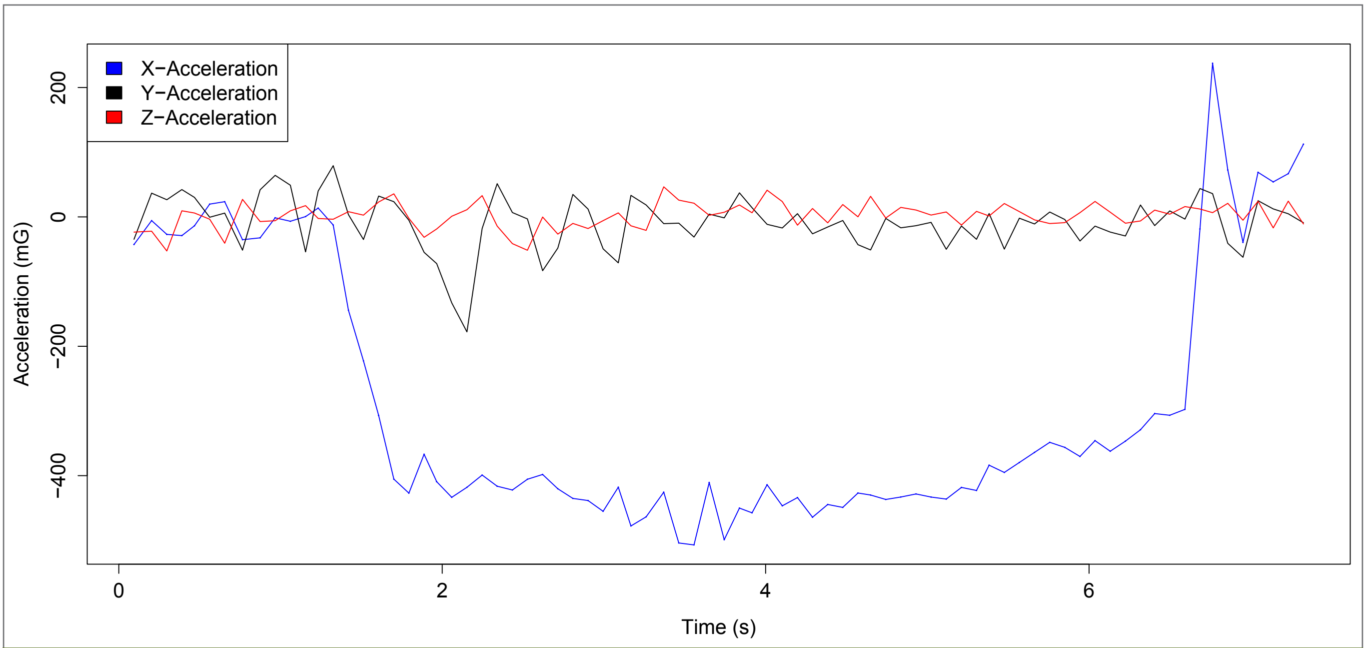

Figure 7: A graph showing the acceleration data for a deceleration from 80 km/h to stationary on a constant incline

smaller accelerations are of concern, such as road quality detection, lane control and swerve detection, and efficient cruise-control algorithms. The vehicle's x-axis acceleration does not notably change due to changes in incline, indicating that the effect of gravity is effectively eliminated and that the resulting acceleration represents an accurate coordinate acceleration and not a proper acceleration.

The acceleration tests also indicated that the vehicle's x-axis, y-axis and z-axis acceleration data vary, independently proving that the resulting acceleration data is rotated accurately to the vehicle's axes. One problem area was identified. The assumption that the effect of a vehicle's yaw with respect to north on reckless driving detection is negligible, adversely affected the operation of the Kalman filter.

PROJECT STATUS

The next step for further advancing this project is a thorough survey of methods for detecting and classifying reckless driving via smartphone, as well as the adaptation of this system to run completely on a smartphone-based platform, with the final goal being the development of a complete and effective smartphone-based reckless driving detection system. A survey titled "Survey of smartphone-based sensing in vehicles for intelligent transportation system applications" has been completed by the authors and is awaiting publication in the *IET Intelligent Transport Systems* journal. The authors' latest work pertains to the development of a complete smartphone-based reckless driving detection system.

CONCLUSION

The goal of this study was to remove the effects of gravitation vector from the acceleration measured by a smartphone in a vehicle. This was done to enable detection of reckless driving behaviour which is primarily based on vehicle acceleration. The objective was met by using the gyroscope, magnetometer, and acceleration sensors with an Unscented Kalman Filter and quaternions to estimate the gravitation acceleration. The estimated gravitation vector is then removed from the acceleration vector measured by the smartphone to determine vehicle acceleration. The results show that the system enables accurate measurement of reckless events under various conditions. A video demonstration of the detector in action in a vehicle can be found at https://youtu.be/c3QpE-namqw, or by scanning the QR code below.

REFERENCE

http://dx.doi.org/10.13140/RG.2.1.3244.4640 ◻

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