Full auto-calibration of a smartphone on board a vehicle using IMU and GPS embedded sensors

Javier Almazán, Luis M. Bergasa, J. Javier Yebes, Rafael Barea and Roberto Arroyo

***Abstract*— Nowadays, smartphones are widely used in the world, and generally, they are equipped with many sensors. In this paper we study how powerful the low-cost embedded IMU and GPS could become for *Intelligent Vehicles*. The information given by accelerometer and gyroscope is useful if the relations between the smartphone reference system, the vehicle reference system and the world reference system are known. Commonly, the magnetometer sensor is used to determine the orientation of the smartphone, but its main drawback is the high influence of electromagnetic interference. In view of this, we propose a novel automatic method to calibrate a smartphone on board a vehicle using its embedded IMU and GPS, based on longitudinal vehicle acceleration. To the best of our knowledge, this is the first attempt to estimate the yaw angle of a smartphone relative to a vehicle in every case, even on non-zero slope roads. Furthermore, in order to decrease the impact of IMU noise, an algorithm based on *Kalman Filter* and fitting a mixture of Gaussians is introduced. The results show that the system achieves high accuracy, the typical error is 1%, and is immune to electromagnetic interference.**

I. INTRODUCTION

A. Motivation

In recent years, the use of smartphones has grown considerably due to their versatility and increasing power of calculation. Smartphones are more than simple cell phones, they are able to send e-mails, connect to the internet, store data and perform many tasks such as a computer does, thanks to their suitable software and hardware. They usually have the following sensors: GPS, cameras, magnetometer, proximity sensor, ambient light, wifi, etc. depending on the model. Moreover, most smartphones have a MEMS IMU (*Micro-electromechanical Systems* and *Inertial Measurement Unit*) composed of an accelerometer and a gyroscope to estimate the device orientation and switch the screen appearance between portrait and landscape views. In this paper, we will focus on the study of these two sensors. The widespread use of smartphones in the world, in combination with the fact that they have many sensors and high computational capabilities, makes them key tools for intelligent vehicle applications [1] and inertial navigation systems [2].

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Smartphones provide two kinds of measurements. The first ones are relative to the world, such as GPS and magnetometers. The second ones are relative to the device, such as accelerometers and gyroscopes. Knowing the relation between the smartphone reference system and the world reference system is very important in order to reference the second kind of measurements globally [3]. In other words, working with this kind of measurements involves knowing the pose of the smartphone in the world.

Intelligent Vehicles can be helped by using in-vehicle smartphones to measure some driving indicators. On the one hand, using smartphones requires no extra hardware mounted in the vehicle, offering cheap and standard sensors for the current vehicles in a direct way. On the other hand, accuracy and precision of smartphone low-cost sensors are very low, although they could be sufficient for some *Intelligent Vehicles* applications. We have to bear in mind that with this approach a portable device is used and its position is not known a priori. Therefore, knowing smartphone pose in the vehicle is mandatory in order to characterize vehicle pose by using smartphone embedded sensors.

B. Related Work

In the field of *Intelligent Vehicles*, kinematics of the vehicle is used to understand the driver state and driving style. This section introduces different techniques to obtain the kinematics of a vehicle as a starting point to monitor driving behaviour.

The most common method to estimate vehicle orientation is using GNSS (*Global Navigation Satellite System*), such as GPS or GLONASS. The heading of the car can be measured by means of two GPS (front-GPS and rear-GPS) [4] or calculating the difference between two consecutive samples using a GPS [5]. These positioning systems have several limitations: the maximum frequency is 1 Hz (at 120 Km/h, a vehicle advances 330 m in 1 s) and they do not work under low visibility of the satellites.

Daily et al. show the strong relation between steering wheel angle and yaw rate of the vehicle using two GPS fixed to the chassis and an IMU in the steering wheel [4]. Yao et al. also use a steering angle sensor to check the accuracy of the heading angle given by a GPS, in order to learn lane change trajectories [6]. Hence, the steering wheel angle is directly related to the kinematics of the vehicle, in particular, to the heading angle. For the purpose of steering wheel angle estimation, bus-CAN data obtained through an OBD-II connector is used in multiple researches [1], [7] and [8]. The main advantage of this approach is that the acquisition frequency is higher than 1 Hz. However, it has two drawbacks. Firstly, it is an invasive method, because it is mandatory to connect additional hardware to the vehicle. Secondly, each automobile manufacturer has proprietary protocols and all of them should be known for a generic and cheap application.

Therefore, the widely used method for measuring the kinematics of a vehicle by using portable devices is based on measuring the Earth's magnetic fields through a magnetometer in combination with other sensors such as GPS or IMU. There are some papers in this line in the state-of-the-art to estimate the orientation of a smartphone on board a vehicle for intelligent vehicle purposes [9], [10] and [11]. The main advantage of this approach is that the increased acquisition frequency is higher than 1 Hz. Nevertheless, the main disadvantage is the significant influence of electromagnetic interferences. The sensitivity of magnetometers is very high, so this sensor does not work properly in a vehicle, because there are many electro-mechanical components that corrupt the measurements. Moreover, measurements provides by a compass are relative to the Magnetic North, not to the Geographic North Pole. The difference between both is the magnetic declination, which varies with time and place.

Besides this, there are some works focused on the fusion of IMU and GNSS measurements to overcome the aforementioned limitations of GNSS. However, the orientation of an IMU in a vehicle must be known a priori to calculate accurate kinematics of the vehicle. Krotak et al. study the acceleration of a vehicle to assess the condition of the driver using only a 3-axes accelerometer [12], and in [13] Di Lecce et al. introduce a system to detect driving patterns using a GPS and a 2-axes accelerometer. In both works, the accelerometer reference system matches with the vehicle reference system, with the purpose of working with meaningful data.

In a general way, we need to know the pose of the smartphone relative to the vehicle coordinate system to correctly merge IMU and GNSS measures. In [14], Niu et al. show a car navigation system using inertial sensors of a smartphone, but the device must be fixed on the dash-board roughly aligned with the vehicle frame. In The Ohio State University, Dai et al. propose an IMU-based method to obtain pitch angle and roll angle of the smartphone relative to the vehicle in order to detect drunk driving [15]. However, they assume that the smartphone is aligned with the longitudinal axis of the vehicle, so the main restriction of this system is that the yaw angle must be null. Finally, Mohan et al. [16], working for Microsoft, present a full-calibration smartphone system on board the vehicle. But it only works if the vehicle is on a flat surface (zero slope), because they base their research on the effect of gravity and decelerations using a GPS to re-orientate the accelerometer data.

The developed IMU based methods share the advantages of magnetometer based methods, because they are sensors embedded in the smartphone with an acquisition rate higher than GNSS based methods, nevertheless, none of these works are able to perform a full-calibration of the smartphone in the vehicle each time that the smartphone is placed on board the vehicle.

C. Contribution

In this paper, we propose a novel system to estimate full auto-calibration of a smartphone on board a vehicle using IMU and GPS embedded sensors. Full calibration provides the position (*latitude, longitude, altitude*) and the orientation (Euler Angles: *pitch, roll, yaw*) of the smartphone relative to the world.

Our main contribution is the method employed to estimate the yaw angle of the smartphone relative to the vehicle coordinate system. This angle is based on longitudinal vehicle acceleration during straight sections of road, processing IMU measurements. We can do this because we are able to decouple gravity and vehicle acceleration measured by the smartphone. In order to decrease the contribution of the IMU noise, we propose to use *Kalman Filter*, in accelerometer and gyroscope measurements, instead of other filtering methods. In spite of filtering the noise, the preliminary yaw angle between the smartphone and the vehicle is inaccurate. Therefore, we propose to apply a fitting mixture of *Gaussians* to increase the exactitude of yaw angle. Finally, full auto-calibration of the smartphone is attached merging the processing IMU and GPS data.

To the best of our knowledge, this is the first attempt to estimate the yaw angle of a smartphone relative to a vehicle in every case, even on non-zero slope roads, using its embedded IMU based on vehicle acceleration. In contrast to the magnetometer based methods, our system is immune to electromagnetic interference. Moreover, the sample frequency is higher than those methods only based on GPS. It is set at 20 Hz, at 120 Km/h, a vehicle advances 1.6 m between consecutive samples, instead of 33 m using GPS at 1 Hz.

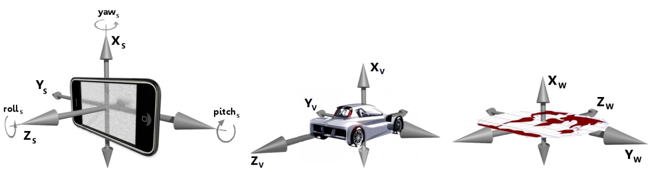
D. Paper Organization

The rest of the paper is organized as follows: in Section II we introduce the reference systems and the system architecture. In Section III, we describe the signal processing used to calculate the vehicle's acceleration and the estimation of yaw angle based on this acceleration. In Section IV we describe the devices used, we evaluate our system in real conditions over an electromechanical goniometer ground-truth and we compare it with a magnetometer-based system. Finally, main conclusions and future work are described in Section V.

II. SYSTEM OVERVIEW

A. Reference Systems

In order to know the kinematics of a vehicle, for intelligent vehicle applications using a smartphone, we must be aware of the relative position between the smartphone and the vehicle and the world. Three reference systems are defined: the smartphone's, the vehicle's and the world's. The three reference systems are defined, as depicted in Figure 1.



(a) Smartphone reference system. (b) Vehicle reference system. (c) World reference system.

Fig. 1. Reference Systems.

Smartphone gyroscopes provide the Euler angles: roll, pitch and yaw. Roll and pitch angles are measurements relative to the world based upon gravity acceleration. Nevertheless, yaw angle is a measurement relative to the position of the smartphone when that sensor is enabled. As that position is unknown, a novel method to obtain the yaw angle is explained in next sections.

B. System Architecture

Achieving a full calibration of an object involves providing its position and orientation relative to a coordinate system. In our case, the position of a smartphone relative to the world is defined by latitude, longitude and altitude, and these values are provided by the embedded geo-location sensor. Analyzing the exactitude or accuracy of these measurements is not the purpose of this paper, we assume it is sufficient using a geo-location sensor based on GPS and GLONASS.

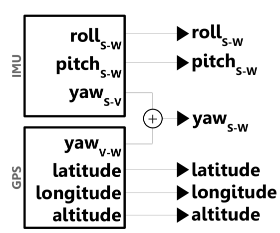


Fig. 2. System architecture.

Regarding the orientation, the roll and pitch angles of the smartphone relative to the world, they are the result of processing the roll and pitch angles provided by the phone. However, estimating the yaw angle of the smartphone relative to the world is more complex. It is the composition of the yaw angle of the vehicle relative to the world and the yaw angle of the smartphone relative to the vehicle. The first one, is obtained based upon two consecutive samples of embedded GPS, and is known as *heading* related to the North Pole. The second one, is estimated using our method to be explained in Section III. Figure 2 shows the architecture of the full auto-calibration system.

III. YAW ANGLE ESTIMATION

When the smartphone is in landscape position, acceleration on the X-axis does not depend on the yaw angle of the smartphone and we estimate the yaw angle using a_{Y_S} and a_{Z_S}. On the other hand, if the smartphone is in portrait position, accelerations on the Y-axis does not depend on the yaw angle of the smartphone and the yaw angle is estimated using a_{X_S} and a_{Z_S}. Therefore, firstly we evaluate if the smartphone is in landscape ($a_{X_S} \geq a_{Y_S}$) or in portrait position ($a_{X_S} < a_{Y_S}$). Figure 3 depicts the main parts of the proposed algorithm. The first step is filtering the accelerometer and gyroscope signals provided by the smartphone (a_{X_S} or a_{Y_S}, a_{Z_S}, $roll_S$ and $pitch_S$). Then we decouple vehicle acceleration from gravity acceleration using trigonometric functions. The next step is to obtain the yaw angle based on a single sample. Finally, the yaw angle between the vehicle and the smartphone is estimated using a *Gaussian Mixture Model* (III-D).

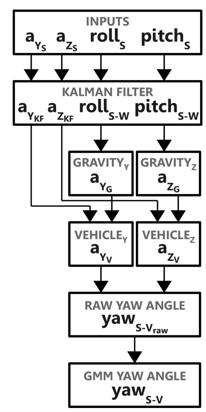


Fig. 3. Yaw angle estimation algorithm (landscape mode, in portrait we use X instead of Y data)

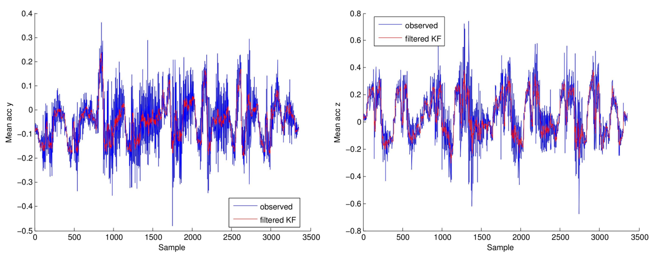
A. Signal Filtering

The main drawback of low-cost embedded sensors is their inaccuracy. High quality sensors add a stability step to provide precise data. However, in our case, the raw accelerometer data is very noisy, as can be seen in Fig. 4 in blue. There are different techniques to process very noisy signals; digital filters [11], median values over a temporal window [16] or Kalman Filter [17]. This last technique is very useful when the noise is white. We have experimentally tested that accelerometer noise is white and a KF has been implemented according to Equation 1.

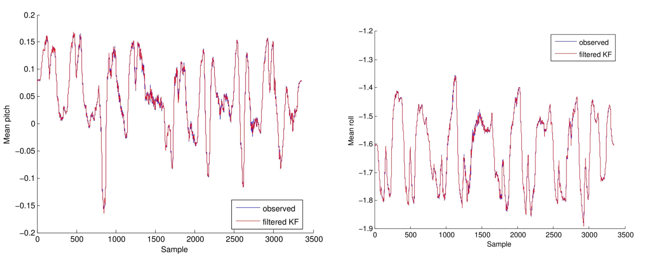
$$\begin{aligned} \mathbf{X}_{t+1} &= \mathbf{F}\ \mathbf{X}_t + \mathbf{w}_t \\ \mathbf{Y}_t &= \mathbf{H}\ \mathbf{X}_t + \mathbf{v}_t \end{aligned} \tag{1}$$

At each sample, the state vector $\mathbf{X}_t$ (acceleration, gyro, and their derivatives) is propagated to the new state estimation $\mathbf{X}_{t+1}$ multiplying by the constant state transition matrix $\mathbf{F}$. The measurement vector $\mathbf{Y}_t$ consists of the information contained within the state vector $\mathbf{X}_t$ multiplied by the measurement matrix $\mathbf{H}$. Moreover, $\mathbf{w}_t \sim N(0, \mathbf{Q}_t)$ is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance $\mathbf{Q}_t$. Likewise, $\mathbf{v}_t \sim N(0, \mathbf{R}_t)$ is the measurement noise with covariance $\mathbf{R}_t$. The experimental value of $\mathbf{Q}$ noise is 10^{-5} for acceleration data, and 10^{-1} for gyro data. The value of $\mathbf{R}$ noise is identity matrix. With these values, the synchronization of the four signals is achieved.

Figure 4 shows the observed input signals in blue, and the estimated signals in red.



(a) Filtering y-acceleration, $a_{Y_{KF}}$. (b) Filtering z-acceleration, $a_{Z_{KF}}$.



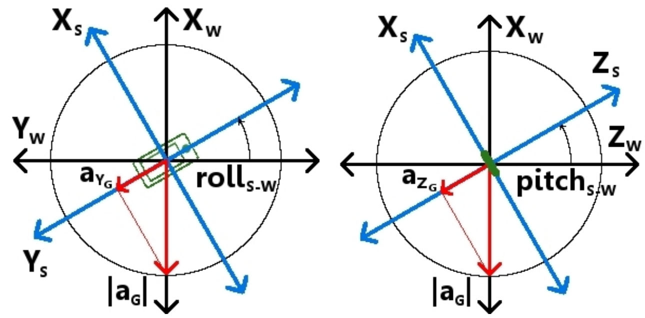
(c) Filtering *pitch* angle, $pitch_{S-W}$. (d) Filtering *roll* angle, $roll_{S-W}$.

Fig. 4. **[Best Viewed in Color]**. Kalman filter.

B. Decoupling Between Gravity Acceleration and Vehicle Acceleration

According to the reference system introduced in Section II-A, when the smartphone is placed on board the vehicle in landscape position, the main weight of gravity acceleration is along the X-axis. However, its acceleration along the Y-axis and Z-axis is not null. The data provided by the embedded 3-axes accelerometer is the result of the sum of two components: vehicle acceleration and gravity acceleration. Thus, this section describes how to decouple both signals.

The gyroscope measures the rotation of the smartphone in relation to the world. Therefore, we project gravity acceleration onto each axis applying basic trigonometry, we assume $|a_G| = 1g$. Our system accounts for $roll_{S-W}$ and $pitch_{S-W}$ angles to obtain gravity acceleration on the Y-axis, a_{Y_G}, and on the Z-axis, a_{Z_G}. It is depicted in Figure 5 according to Equations 2 and 3. In static landscape orientation, the $roll_s$ and $pitch_s$ angles will be null.



(a) Gravity acceleration on Y_S. (b) Gravity acceleration on Z_S.

Fig. 5. **[Best Viewed in Color]**. Extracting gravity acceleration. The world reference system is in black, the smartphone reference system is in blue, the gravity acceleration is in red and the smartphone is in green.

$$a_{Y_G} = \sin(roll_S)\,|a_G| \tag{2}$$
$$a_{Z_G} = -\sin(pitch_S)\,|a_G| \tag{3}$$

Afterward, vehicle acceleration (a_{Y_V} and a_{Z_V}) is calculated by subtracting gravity acceleration from the filtered acceleration ($a_{Y_{KF}}$ and $a_{Z_{KF}}$), using Equations 4 and 5.

$$a_{Y_V} = a_{Y_{KF}} - a_{Y_G} \tag{4}$$
$$a_{Z_V} = a_{Z_{KF}} - a_{Z_G} \tag{5}$$

C. Yaw Angle Based on Single Sample

When the vehicle moves in a straight line, no lateral acceleration in the reference system of the vehicle can be assumed. Therefore, the composition of a_{Y_V} and a_{Z_V} gives the vector of the vehicle acceleration in the reference system of the smartphone. As a result, the computation of the yaw angle between vehicle and smartphone is calculated. This is showed in Figure 6 according to Equation 6.

$$yaw_{(V-S)_{raw}} = \begin{cases} \arcsin\left(\frac{a_{Z_V}}{|a_{YZ_V}|}\right) & \text{if } a_{Y_{KF}} >= 0 \\ \pi - \arcsin\left(\frac{a_{Z_V}}{|a_{YZ_V}|}\right) & \text{otherwise} \end{cases} \tag{6}$$

where

$$|a_{YZ_V}| = \sqrt{|a_{Y_V}|^2 + |a_{Z_V}|^2}$$

The yaw angle is only based on the current sample. We know it as raw yaw angle because it is a preliminary value.

To enforce the fact that the car moves in a straight line, we impose four conditions to apply this method. The first one is that the yaw angle variation of the smartphone, Δyaw_S, will be less than 0.04° -threshold

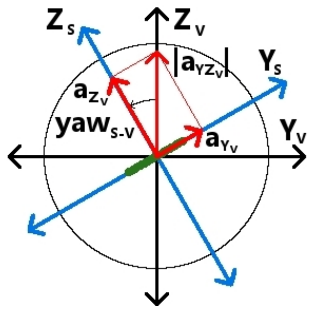


Fig. 6. **[Best Viewed in Color]**. Yaw angle based on single sample. The vehicle reference system is in black, the smartphone reference system is in blue, the vehicle acceleration is in red and the smartphone is in green.

fixed based on sensor noise. Moreover, in order to avoid incorrect estimations of $yaw_{(V-S)_{raw}}$, the variation between consecutive samples of pitch and roll will be less than one degree (due to bumps or potholes in the road), $\Delta roll_S \leq 1°$ and $\Delta pitch_S \leq 1°$. As we use vehicle acceleration to get the yaw, we set a fourth condition: if the acceleration $|a_{YZ_V}|$ is less than 0.4 Km/h, the system does not compute $yaw_{(V-S)_{raw}}$ because the noise corrupts the IMU measurements. Figure 7 shows the results, taking into account all conditions in a sequence of 3 minutes with many acceleration-brake events. The depicted signal is quite unstable, with high variation. In Section III-D a solution is proposed.

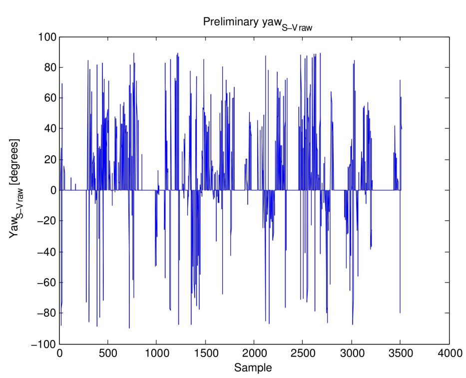


Fig. 7. Yaw angle based on single sample with straight line conditions.

D. Yaw Angle Estimation Based on Stochastic Methods

In spite of filtering the input signals and forcing the aforementioned conditions, the preliminary $yaw_{(V-S)_{raw}}$ signal is not very accurate. The reason is that the method used to decouple the vehicle and gravity acceleration is simple and it does not take into account the noise of the sensors. Consequently, the preliminary signal continues to be affected by the effect of vehicle and gravity acceleration. In order to optimally decouple these two contributions, a stochastic method based on fitting mixture models of Gaussian functions is proposed.

Expectation-Maximization (EM) algorithm is a well established maximum likelihood algorithm for fitting a mixture model to a set of data [18]. It should be noted that EM requires *a priori* selection of model order, namely, the number of M components to be incorporated into the model. The probability density function in the form of a Gaussian Mixture distribution with 2 mixtures provides one Gaussian centered on the best estimate of yaw angle $yaw_{(V-S)}$, corresponding to the vehicle contribution, and the other to gravity contribution.

At each significant event, accelerating or breaking, the system stores preliminary values of yaw angle, $yaw_{(V-S)_{raw}}$. In order to design an accurate system, the EM algorithm starts to estimate $yaw_{(V-S)}$ after 100 values (applying the stochastic method in a set of few data does not provide a significant value of yaw angle). We assume this short transition of 100 values is not relevant for *Intelligent Vehicle* purposes. For each set of samples, the algorithm chooses the model with minimum covariance and maximum amplitude as the optimum yaw angle $yaw_{(V-S)}$. Figure 8 depicts the result of GMM-EM algorithm based on minimum covariance.

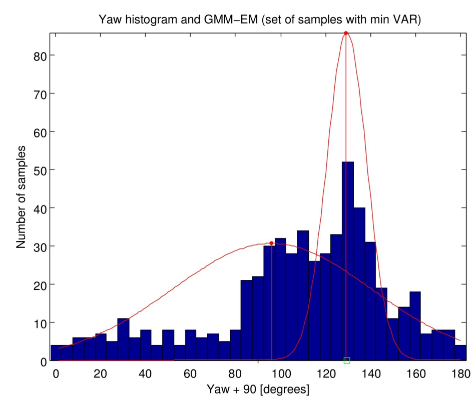


Fig. 8. **[Best Viewed in Color]**. Normalized histogram of $yaw_{(V-S)_{raw}}$, in blue, and Gaussian models using GMM-EM algorithm, in red. The estimated value of $yaw_{(V-S)}$ is drawn as a green square. Note: abscissa axis shows $yaw_{(V-S)}+90°$

IV. EXPERIMENTAL RESULTS

A. Smartphone Embedded Sensors

In the recent report published by *Pew Internet & American Life Project* [19], nearly half of American adults are smartphone owners. The most used smartphone operating system in USA is Android (38%) followed closely by iOS (36%). Nonetheless, in contrast to the heterogeneity of the sensors of the smartphones running Android (the sensors depend on the manufacturer and on the model), latest versions of smartphones of Apple have the same accelerometer and the same gyroscope. Consequently, these devices have been used in many researches [1], [2], [11], [14], [20] and [21]. Therefore, to carry out the proposed system we chose an iPhone 4 and an iPhone 4S.

Since June 2008 Apple has mounted the LIS331DLH accelerometer in its devices. It is a MEMS ultra-low power digital 3-axis accelerometer provided by STMicroelectronics. According to the datasheet, it has dynamically user selectable full scales of $\pm 2g$, $\pm 4g$ and $\pm 8g$ (Apple configures it in a $\pm 2g$ range) and it is capable of measuring accelerations with output data rates from $0.5Hz$ to $1kHz$. Moreover, the bandwidth is $25Hz$ and the acceleration noise density is $218\mu g/\sqrt{Hz}$.

The L3G4200D gyroscope mounted in the iPhone is also provided by STMicroelectronics. It is a MEMS ultra-stable 3-axis digital output gyroscope, and it is used to determine the rotation rate. Integrating this data over time the three Euler Angles of the smartphone (pitch, yaw and roll) can be estimated. According to the datasheet of the manufacturer it has a full scale of $\pm 250dps$, $\pm 500dps$ and $\pm 2000dps$ and it is capable of measuring rates with a user-selectable bandwidth. Apple configures the rotation rate in a $\pm 250dps$ range, for a gyroscope noise density of $0.03dps/\sqrt{Hz}$ and a bandwidth of $50Hz$.

B. Data Acquisition

The common framework of Apple to read the values of the motion sensors could be quite confusing. They provide preprocessed signals without bias, such as the variable *motionRate* for the gyroscope, and the variable *userAcceleration* without the influence of gravity acceleration for the accelerometer. However, these signals are not valid for dynamic environments, because the acceleration of the vehicle is confused with gravity acceleration. Thus, we propose to work with raw data of the sensors, such as *acceleration (x, y, z)* and *attitude (yaw, pitch, roll)*. As Shanklin et al. explain in [20], the integration based method to obtain the Euler Angles involves drift in the measurements. But, surprisingly, it is very low, almost nonexistent for the pitch and roll angles, because iPhone already implements an algorithm to remove the drift using the direction of the gravity obtained from the accelerometer. In our system, the maximum acquisition frequency is set at $20Hz$, 20 times higher than GPS and most smartphone processors are able to achieve it.

C. Experiments

For the evaluation of the system that has been developed, a high quality electromechanical goniometer is used as ground-truth. The goniometer is an instrument for measuring angles with great precision and is commonly employed in optical communications. Figure 9 shows the holder mounted in the middle of the windshield of the car, which matches with the vehicle reference system.

The experiments were performed with two devices (iPhone 4 and iPhone 4S) to assess differences in the processing capabilities of each phone. Moreover, to check the quality of our system, we carried out sweeps from $-50°$ to $50°$, in increments of ten degrees. For each angle, we drove more than 2 hours. In Table I we show the results obtained (average error, ε_{avg}, and standard deviation, σ) in more than 44 hours of driving.

(a) System mounted on the vehicle. (b) Electromechanical goniometer.

Fig. 9. Goniometer based ground-truth.

yaw_{S-V}	iPhone 4		iPhone 4S	
	$\lvert\varepsilon_{avg}\rvert$	σ	$\lvert\varepsilon_{avg}\rvert$	σ
$-50°$	2.23%	1.31%	0.81%	1.69%
$-40°$	1.28%	0.84%	1.05%	1.02%
$-30°$	1.19%	0.71%	1.17%	0.94%
$-20°$	0.84%	0.73%	1.03%	0.76%
$-10°$	0.89%	0.52%	0.29%	0.46%
$0°$	0.93%	0.96%	0.20%	0.43%
$10°$	0.59%	0.72%	0.39%	0.11%
$20°$	0.67%	0.42%	0.72%	0.66%
$30°$	0.77%	0.45%	0.96%	1.57%
$40°$	0.89%	3.23%	1.07%	0.80%
$50°$	1.73%	2.34%	0.62%	2.33%
Typ	**1.09%**	**1.11%**	**0.76%**	**0.98%**

TABLE I

Error and typical deviation using iPhone 4 and 4S.

Overall, the results achieved are quite accurate. In spite of both devices having the same sensors, there are slight differences between their results. iPhone 4 is less precise than iPhone 4S. The reason is that they have different CPU, iPhone 4S is able to provide samples at $20Hz$, whereas the acquisition frequency of iPhone 4 is near $14Hz$, sometimes falling to $3Hz$. The typical error, $|\varepsilon_{typ}|$, of iPhone 4 is 1.09% (equivalent to 3.9°) and the typical error of iPhone 4S is 0.76% (equivalent to 2.7°). The standard deviation, σ, is approximately 1%. Notice that when the yaw angle is less than 10°, the error of iPhone 4S is less than 1.5°.

Moreover, the estimated yaw angle of the smartphone relative to the vehicle in combination with embedded geo-location sensor based on GPS and GLONASS, achieve the full auto-calibration of a smartphone relative to the world, as it was depicted in Figure 2. For the evaluation of the whole system, the obtained yaw angle is compared

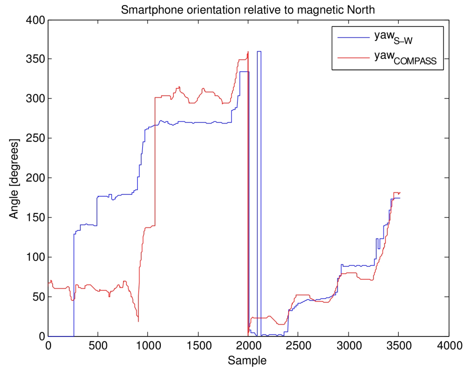


Fig. 10. **[Best Viewed in Color]**. Comparison between our system and the system based on magnetometer.

to the one based on magnetic fields. Figure 10 shows the comparison between our system and the system based on magnetometer, magnetic declination is taking into account in order to reference both signals to Geographic North Pole. The magnetic-based method shows bias, fluctuations, gaps and offset. Therefore, our proposed system has higher accuracy.

V. CONCLUSIONS AND FUTURE WORK

The proposed system, based on vehicle acceleration measurements, is able to estimate the yaw angle of a smartphone relative to the vehicle using the embedded IMU of an iPhone. In other words, this work has presented a novel auto-calibration method for low-cost IMU. To the best of our knowledge, this is the first work that is able to achieve the pose of a smartphone in a vehicle using the low-cost inertial sensors instead of the digital compass. The main advantage is that our approach is robust against electromagnetic interferences.

Furthermore, the Gaussian Mixture Models technique applied to a yaw histogram, significantly improves the accuracy in yaw angle estimation, because it is able to decouple vehicle acceleration from gravity acceleration.

Further research could be extensive. Knowing the full pose of the smartphone relative to the world opens the door to INS (*Inertial Navigation Systems*) for intelligent vehicle purposes. Moreover, in the future, our contribution could be applied to detect the kinematics of the vehicle to estimate driver state (inattention, drowsiness or drunken state).

VI. ACKNOWLEDGMENTS

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