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A Preliminary Study on Attitude Measurement Systems Based on Low Cost Sensors

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Abstract. The increasingly use of Autonomous Underwater Vehicles (AUVs) in several context led to a rapid development and enhancement of their technologies, allowing the automatization of many tasks. One of the most challenging tasks of AUVs still remains their robust positioning and navigation, since classical global positioning techniques are generally not available for their operations. Inertial Navigation System (INS) methods provide the vehicle current position and orientation integrating data acquired by the internal accelerometer and gyroscope. This system has the advantage of not needing to either send or receive signals from other systems; however, among the errors the sensors are mainly affected by, the most critical one is related to their drift, which makes the position error growing over time. The attenuation of the effect of these problematics is generally achieved combining different positioning methods, as for example acoustic- or geophysical-based ones. An accurate estimation of the device orientation is anyway necessary to get satisfying results in terms of position and autonomous navigation. In this paper, a preliminary study on the use of smartphone low-cost sensors to perform attitude estimation is presented. With the final aim of developing a cheaper and more accessible underwater positioning system, a first analysis is conducted to verify the accuracy of the attitude angles obtained by the integration of smartphone data acquired in different operative settings. Different filtering methods will be employed.

Keywords: Orientation estimation · Low-cost sensors · Filtering methods

1 Introduction

AUVs have demonstrated versatile capabilities to conduct missions in several fields, as for example oceanographic research, surveillance and defense, demining, underwater energy development, bathymetric data collection, etc., for which high accuracy of measured data is required. Vehicles autonomy stands as one of the most important and at the same time critical point for their development and usage: in the last years, remarkable results have been reached in the field, and the technological development is continuously growing to enhance the vehicles performances.

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Being localization and navigation a fundamental part of the autonomy of the AUV, optimizing the algorithms and techniques underlying these processes is crucial. The rapid attenuation of radio signal together with the unstructured nature of the undersea environment makes traditional methods (based on Global Navigation Satellite System, GNSS) not suitable for the AUV control; hence, the design and implementation of navigation systems still constitute one of the most challenging tasks [1]. Modern AUV localization techniques are classified into three main categories: Acoustic Positioning Systems, Geophysical Navigation (GN) and Inertial Navigation System (INS) methods. Ultra-Short Base Line (USBL)-aided buoy is a novel approach to underwater acoustic localization, where the USBL device used to obtain the position of the target is housed in the buoy itself. In this case, Inertial Measurement Unit (IMU) and Differential-GPS (DGPS) are exploited to refer the measures to the current buoy position. Results evidenced that the buoy motion has an effect on the overall accuracy of the localization and particularly the yaw angular rate affects the azimuth measurement [2].

This confirms that the orientation estimation generally provided by inertial systems is fundamental for an accurate positioning process; nevertheless, high accuracy results usually requires high cost instrumentations.

In this paper, the use of low-cost sensors mounted on common smartphones is evaluated as an alternative approach to more expensive INS, in order to further measure the orientation of the device. Several filtering techniques have been tested on data acquired by the gyroscope, accelerometer and magnetometer of an iPhone device. A preliminary evaluation of the proposed method is conducted on the basis of statistical parameters calculated by the analysis of the estimated and ground truth values.

2 Underwater Positioning Systems

The practically impossible use of the GNSS together with the unstructured and hazardous characteristics of the marine environment makes the development of AUVs a very challenging scientific and engineering problems. Different navigation and positioning methods have been studied by researchers, resulting in three main categories of underwater techniques: acoustic, geophysical and INS based methods.

In the first case, localization is achieved by measuring ranges from the Time of Flight (TOF) of acoustic signals (which have a lower absorption rate in the water than radio frequency signals). Three different approaches can be employed, based on the length of the baseline between the transducers: in a long baseline (LBL) system the instruments are more than 100 m spaced over a wide area on the sea floor; in a short baseline (SBL) system, the transducers are placed at the opposite ends of a ship's hull, thus not exceeding 20 m of distance, while for super short or ultra-short baseline (SSBL and USBL) the length among them is smaller than 10 cm. Usually, the system has one transponder and at least three transducers and its deployment depends on the mission: for example, USBL and SBL are more suitable for tracking mission and short-range navigation. Variability of the water characteristics and accordingly of the sound speed, environmental noises and multipath can reduce the performance of these systems, which can also be complex to deploy.

Conventional dead-reckoning (DR) techniques can provide optimal results, especially if combined with geophysical navigation. The latter is based on environmental-observed effects (i.e. terrain topography, gravity anomalies and geomagnetic field variations, acquired by cameras, ranging sonars or magnetometers) and can provide accurate position estimates and low localization errors in the long run with relatively low-cost implementations [3, 4]. One of the implementation of the underwater GN is the terrain-aided navigation (TAN), based on the matching between a set of range measurement acquired by the sensors onboard and a previously acquired digital elevation map (DEM) of the terrain to estimate the vehicle's position. This method is able to mitigate the accuracy drifts of the inertial systems but heavily depends on the need for high-quality geophysical maps before the missions, other than being computationally costly when comparing and matching the map with sensors data.

Simultaneous Localization And Mapping (SLAM) techniques deal with this problem: they allow the AUV to acquire a map of the environment while simultaneously localizing itself basing on the acquisition. The actual methods represent a robust solution for static and limited-size areas reaching sub-metrical precision, but cannot accomplish the task for dynamic, unstructured or large-scale environment [5].

As mentioned before, the use of inertial sensors is typically considered as the central navigation system of AUVs. It contains an inertial measurement unit (IMU) which allows the measurement of linear acceleration and angular velocity by its three orthogonal rate-gyroscopes and -accelerometers respectively. These are integrated to obtain the instantaneous speed and position of the vehicle without the need for external references. Unfortunately, several problems are associated with these sensors: gyroscopes measure angular rate of change and not angular position directly and accelerometers measure more than just linear acceleration (e.g. gravitational acceleration and Coriolis terms); measurements are noisy and biased and body-frame states need to be transformed to the inertial reference frame (e.g. Euler angles) [6]. Moreover, as already stated, the IMU errors increases over time due to the drift of the sensors. The errors accumulation is theoretically linear for heading and velocity and exponential for position [7]. This means that the navigation information provided by the INS can be considered reliable and accurate only within short times, while it is still impossible for a pure inertial navigation system to maintain the high-precision level throughout a mission. That is why external information and measurement constitute an effective improvement to navigation accuracy.

Moreover, even when high-end INS provide high accuracy, their high cost and complexity place constraints on the environments in which they are practical for use, leading to the development and consequent employment of MEMS (Micro Electro-Mechanical Systems) AHRS (Attitude Heading Reference System). Characterized by light weight and small sizes, they integrate a magnetometer to the INS configuration, thus being able to measure the variation of the Earth's magnetic field to estimate the best attitude of the vehicle [8, 9]. Examples of AHRS are smartphones and video game consoles; it should be noted that mobile devices are able to instantly calculate pose estimation using their integrated sensors. In this way, these devices have the potential to be used in several applications beside orientation estimation, like geomatics, augmented reality (AR), etc.

3 Sensors and Algorithms

Today's smartphones incorporate numerous sensors, which may include compass, accelerometer, gyroscope, GPS, camera and sensors of temperature, pressure, proximity, etc. It should be considered that smartphone applications cannot directly access physical sensors embedded into smartphones: the raw signal they measure is processed by the operating system and then made available to the applications in a standardized format (the smartphone sensor). That means that the technical specifications of the sensors cannot be obtained from the manufacturer's data sheet [10], but a general and accurate review of their functioning can be easily found.

3.1 Smartphone Sensor Accuracy

In [10], for example, a sensing application for analyzing accelerometer and gyroscope bias and noise parameters (as starting point) of some of the most common smartphones of the recent years is presented. The iPhone model employed in this experiment is not included in the list, but some general information can be derived from the overall analysis. In particular, an extract by [10] (Table 1) reports the average and the standard deviation of the measured smartphone accelerometer and gyroscope biases.

Table 1. Statistical parameters of the absolute bias values of smartphone sensors [10].

	Accelerometer $[mg_0]$			Gyroscope $[mrad/s]$		
	X	Y	Z	X	Y	Z
Average	14.3	14.6	25.3	9.4	8.7	6.1
StDev	14.2	15.2	25.1	13.6	12.1	8.7

In [11], a static test made through the acquisition of the raw angular velocities and accelerations was performed made to test the stability of the sensors of an iPhone 4. A summary of this test is reported in Table 2, confirming good stability for both the gyroscope and the accelerometer. This result can be projected to the iPhone SE as a really good basis, being its technology surely more advanced than that of its earlier version.

Table 2. iPhone 4 sensors stability performance derived from a static test [11]

	Accelerometer $[g_0]$			Gyroscope $[rad/s]$		
	X	Y	Z	X	Y	Z
RMSE	2.8	2.4	4.2	4.8	3.2	4.3

The low-cost MEMS AHRS sensors of the smartphone are simply strapped to the unit, so that the coordinate frame of each of them has the same directions. This configuration provides much sensitivity to the turning rates but less stability. The raw data acquired by the sensors can have possible errors due to the system design;

moreover, they are affected by thermal and electronic-related noise, usually modelled as additive Gaussian noise. This entails deviations and oscillations around the correct value that can be reduced by prior calibration procedures. However, additional considerations must be made on the sensors [12]. The accelerometer at rest should measure the gravitational acceleration only but, being the sensor very sensitive to vibration and mechanical noise, it will measure the result of many additional forces besides gravity, with consequences on the final estimation. The output of a magnetometer largely depends on the environment additional magnetic fields, which can affect the accuracy of the results. Gyroscope measures the angular rate of change around the three axes in the body frame, which could be integrated to get the angular positions. Unfortunately, even if less sensitive to perturbations and not influenced by external factors, the gyroscope is not free from errors [13]. They are generally caused by the non-perfect symmetricity of the oscillation plane, by the dissipation of the vibration mechanical energy in thermal energy and by the non-linearity of the restoring forces. As an intrinsic characteristic of the gyroscope, these errors accumulate over time, becoming unbounded in magnitude: this is commonly known as gyroscope drift.

The integration of the three sensors can compensate the different errors related to each of them to obtain a complete orientation measurement [14]. The complementary filter, for example, combines the accelerometer good performance in static conditions with those of the gyroscope in dynamic ones. Two filters, a low-pass and a high-pass, are used on accelerometer and gyroscope data respectively [15]. The Kalman filter, also known as Linear Quadratic Estimator (LQE), is the optimal state estimator for any linear stochastic system subject to known normally distributed state and measurement noise. This filter does not only consider the sensor measurements but also the underlying dynamics of the system itself; for these reasons it is widely used to solve many tracking and data prediction tasks. Other implementations as the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) extend these techniques to nonlinear systems [16]. A brief overview on the Kalman filter will be given in the next paragraph to better understand its functioning, while the experiment setup will be analyzed in chapter 4.

3.2 Kalman Filter: An Overview

The Kalman filter is a predictive filter which uses a recursive algorithm to estimate the state of a dynamic system by elaborating sequential measurements. In the discrete time setting, a time-invariant system can be described by a state Eq. (1) and a measurement Eq. (2). In (1) $\vec{x}_t$ is the state vector to be predicted, $\vec{x}_{t-1}$ and $\vec{u}_{t-1}$ are the state and the input vectors at the previous time. A and B are the system matrices, which respectively relate the current states and the inputs to the next states and are assumed stationary over time. The actual measurements can be modelled as in (2): $\vec{y}_t$ is the measure and C is the matrix which relates the system state to the measured one. $\vec{w}_{t-1}$ and $\vec{v}_t$ are the additive process and measurement noise respectively, assumed to be zero-mean Gaussian processes.

$$\vec{x}_t = A\vec{x}_{t-1} + B\vec{u}_{t-1} + \vec{w}_{t-1} \tag{1}$$

$$\vec{y}_t = C\vec{x}_t + \vec{v}_t \tag{2}$$

The Kalman filter equations provide a prediction (3), (4) and an update (5), (6), (7), (8) phases.

$$x_t^{'} = A\vec{x}_{t-1} + B\vec{u}_{t-1} \tag{3}$$

$$P_t^{'} = AP_{t-1}A^T + Q \tag{4}$$

$$S = CP_t^{'}C^T + R \tag{5}$$

$$K_t = P_t^{'}C^T S^{-1} \tag{6}$$

$$x_t = x_t^{'} + K_t\left(y_t - Cx_t^{'}\right) \tag{7}$$

$$P_t = (I - K_t C)P_t^{'} \tag{8}$$

The a-posteriori state estimate x_t is obtained as a linear combination of the a-priori estimate $x_t^{'}$ and a weighted difference between the actual measurement and the prediction, $K_t\left(y_t - Cx_t^{'}\right)$. The difference in (7) is called measurement innovation or residual and reflects the discrepancy between the predicted measurement and the actual measurement. K is known as the Kalman gain and minimizes the a-posteriori error covariance; P is the error covariance matrix initially set by the user and updated by the filter. Q and R are the covariance matrices of the process and measurement noise respectively. Q indicates the uncertainty about the model dynamics, while R depends mainly on the sensors used in the systems: large values in both the matrices means greater noise levels. As both Q and R greatly affect the final filter performance, a tuning procedure of their values is important, as the true noise statistics are unknown.

4 Experiments and Results

4.1 Coordinate Frames and Smartphone Details

The data collection has been made through the Matlab R2019b Mobile App running on an iPhone SE mobile phone, both in static and dynamic conditions. The orientation is defined by the three angles of Azimuth, Pitch and Roll: to understand and analyse the results of the orientation estimation it is important to point out that Matlab provides measures in a custom body coordinate frame while requiring data in North-East-Down (NED) frame for its underlying functions (Fig. 1). In fact, underwater applications are performed in NED coordinate frame: the positive X-axis points to the North, the positive Y-axis to the East, and the positive Z-axis follows the positive direction of the gravity force. Smartphone data loaded in Matlab is instead expressed in a different body frame, where the positive X-axis extends out of the right side of the phone, positive Y-axis out of the top side, and the positive Z-axis out of the front face of the phone, independently of the actual smartphone orientation. Thus, an appropriate coordinate transformation is needed in order to switch pass from body frame to the NED frame. With this state, the Euler angles are defined as follows: the Azimuth is the angle between the magnetic north to the positive Y-axis, measuring the rotation around the Z-axis of the phone; it will be indicated by θ. The Roll is considered as positive when the Z-axis of the smartphone (laying on a flat surface) begins to tilt towards the positive X-axis and, in the same way, the positive Pitch is defined when the positive Z-axis begins to tilt towards the positive Y-axis. The related angles will be indicated by φ and ψ.

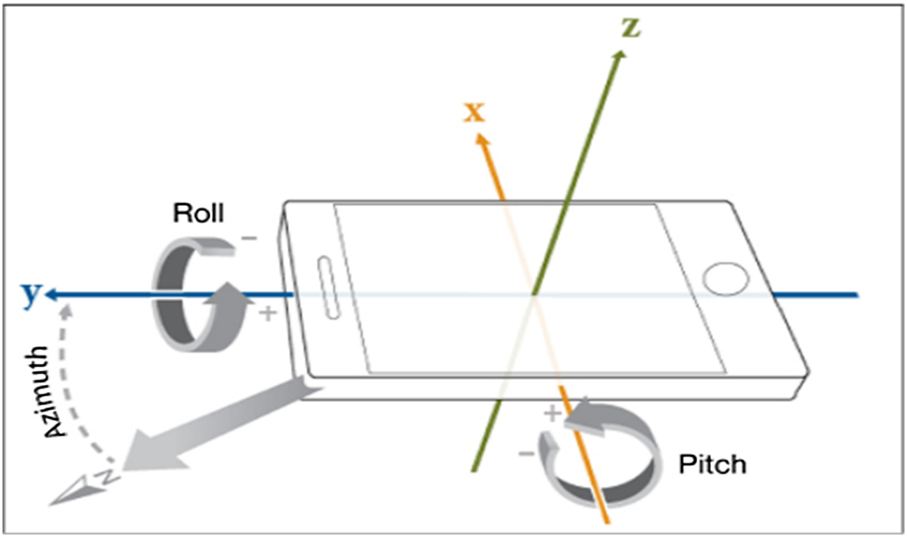

Fig. 1. Coordinates frame required for the use of Matlab built-in functions [17].

4.2 Experiment Setup and Results

Some of the built-in functions of Matlab have been used to combine the sensors measurements. It follows a brief overview [18].

The “ecompass” function combines the accelerometer and magnetometer data and returns a quaternion which can rotate the quantities from the NED frame to a child frame; the orientation angles can be simply obtained applying the “eulerd” function to the quaternion, specifying the correct axis order. The “imufilter” creates a system object characterized by nontunable properties (unless otherwise indicated). These are the sample rate of input sensor data (Hz), the decimation factor, the variance of the gyro signal noise and offset drift ($(\text{rad/s})^2$), the variance of accelerometer signal and of the linear acceleration noise ($(\text{m/s}^2)^2$), the decay factor for the linear acceleration drift and the covariance matrix for process noise. Applying this object to the gyro and accelerometer readings, the orientation and angular velocity are computed. This algorithm assumes that the device is stationary before the first call.

The "AHRSfilter" function creates an object which allows to fuse the data provided by accelerometer, gyroscope and magnetometer to obtain orientation and angular velocity. The properties of this filter are the same as the imufilter, with the addition of the variance of the magnetometer signal noise and of the magnetic disturbance noise (μT^2), the decay factor for magnetic disturbance and the expected estimate of the magnetic field strength (μT).

The "complementaryFilter" function, as the previously analyzed filters, returns a System object which is applied to the accelerometer, gyroscope and magnetometer readings to give the orientation of the device. The parameters of this filter are the sample rate (Hz), the accelerometer and magnetometer gains and the output orientation format. The magnetometer input is enabled by default but can be disabled if needed.

The aim of the experiment was to test the smartphone performance in basic configurations, in order to evaluate if the accuracy of the reliability of the results could match a further use of the same device in more complex settings. For this reason, the toy-experiment has been conducted in two different phases. In the first one, the smartphone was placed in a static configuration on a flat surface, avoiding any form of disturbance which could have altered the acquisition. This was made to verify the reliability of the measurements in static mode, where no external noise should affect the acquisition. Stated this, in the second part of, the experiment the smartphone has undergone several rotations on the same flat surface, each time around one of its three axes. Again, to better evaluate and particularly see the response of the sensors, a 90° rotation has been chosen as the most elementary test.

The modalities have been the same for both the phases. Having enabled the sensors, five minutes acquisition have been performed; the resulting readings were automatically sent to the Matlab Drive to be further processed in the desktop version of the software. The orientation parameters given by the smartphone itself were acquired too and then set as the ground truth for the experiment.

The first part of the script allowed the synchronization of the acquisitions, which were then transformed in the required frame to be correctly processed through a coordinates transformation. The orientation angles of Azimuth, Pitch and Roll have then been estimated using each of the Matlab function above mentioned: a first evaluation of their accuracy has been made on the basis of the resulting standard deviation.

At this point, an elementary Kalman filter has been implemented. The state and bias vectors have been initialized as zeroes arrays: the gyro biases will be calculated and subtracted to the state with the aim to reduce the gyro drift. The transformed angular rates of change have been used to get roll, pitch and yaw angles as input vector, while the state update was processed using the results of the magnetometer and accelerometer integration.

As previously said, the Q and R matrices needed a fine tuning, indispensable to obtain the least possible oscillation around the reference values (those directly measured and smoothed by the phone, referred to as ground truth). For this reason, a fuzzy logic-based method has been followed to minimize the standard deviation [19], changing the matrices values and evaluating the parameter variation after each step. This preliminary tuning phase assured a correct estimation of the Euler angles by the Kalman filter.

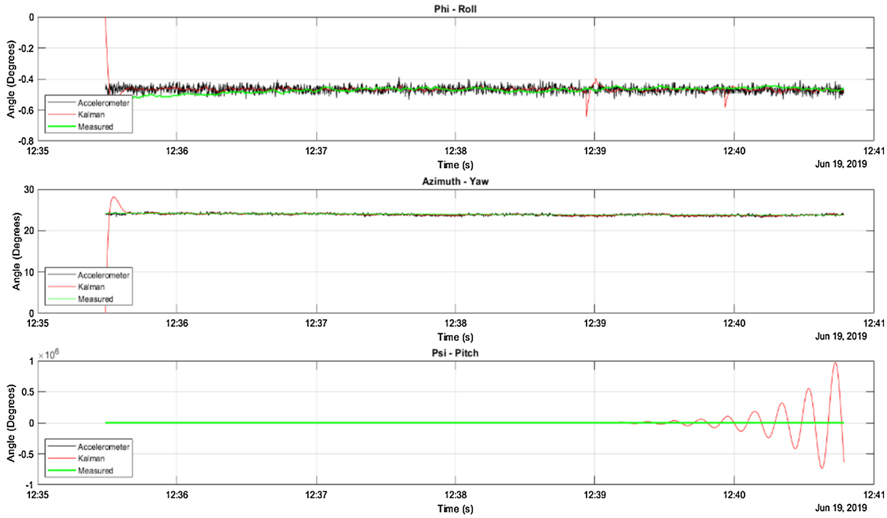

Fig. 2. Kalman filter estimation of the Euler angles. (Color figure online)

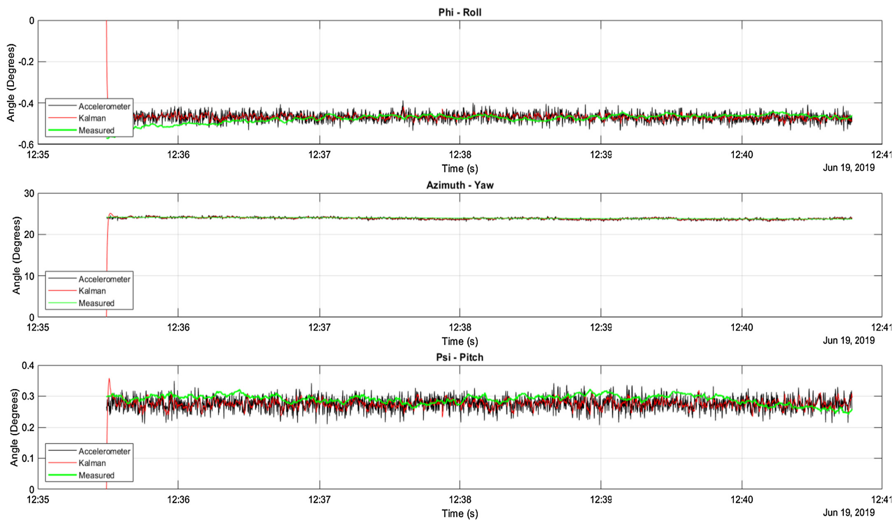

Fig. 3. Kalman filter estimation of the Euler angles after the tuning process.

Figure 2 and Fig. 3 show the results of the finetuning for the static experiment. Although an oscillation in the first part could be tolerated, being due to the normal initial settling of the filter, continued successive fluctuations evidence a wrong tuning, particularly if characterized by abnormal amplitudes as those visible in the third section of Fig. 2, related to the Pitch estimation made by the KF (in red). The enhancement provided by a correct tuning can be seen in Fig. 3, where no excessive oscillations characterize the evaluation trend of the Kalman filter. After the tuning (Fig. 3), the KF has been used with different inputs, in order to verify the contribution of each sensor in the estimation. The evaluation has been made analysing the root mean square, the mean and maximum deviations between the reference Euler angles values and the estimated ones. Results (Table 3 and Table 4) show that in general the complementary filter gives the best estimation, with the ecompass filter producing better results in few cases; nevertheless, the magnitude of the values confirms that both the Matlab filters run with very good performances, estimating the Euler angles with smaller errors than the others. This result exactly matches what previously said about the errors compensation of each sensor made through the combined integration of their measures.

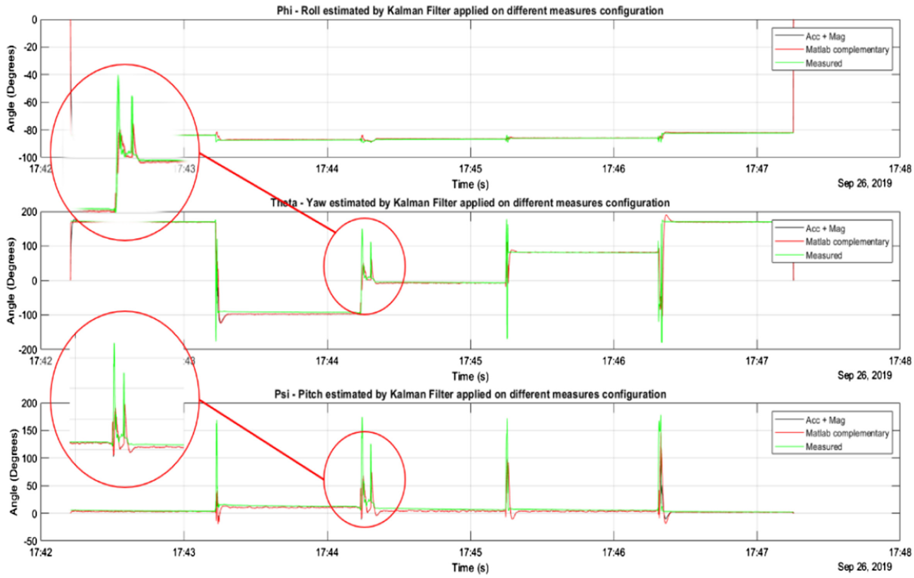

Fig. 4. Kalman filter estimation of the Euler angles in dynamic conditions: 90° rotation around the Z-axis. (Color figure online)

Table 3. Statistical evaluation of the Kalman filter performance applied on the Matlab "Complementary" filter

	Root mean square $[10^{-3}\text{deg}]$	Mean deviation $[10^{-3}\text{deg}]$	Maximum deviation $[10^{-3}\text{deg}]$
Roll (φ)	33.4686	16.9271	571.7200
Azimuth (ϑ)	626.1838	86.8802	379.4724
Pitch (ψ)	22.5467	8.5153	84.9020

Table 4. Statistical evaluation of the Kalman filter performance applied on the Matlab "ecompass" filter

	Root mean square [10^{-3}deg]	Mean deviation [10^{-3}deg]	Maximum deviation [10^{-3}deg]
Roll (φ)	31.6038	7.7425	571.7200
Azimuth (ϑ)	830.8329	101.3869	968.4521
Pitch (ψ)	26.0136	14.8977	58.3436

Figure 4 shows the sensors response to one of the dynamic test made, in which the smartphone has been subjected to a 90° rotation around the Z-axis. The ecompass and the complementary filter plotted in the pictures have quite the same response, as demonstrated by the fact that the black line representing the first function is only rarely visible under the red line of the latter. Moreover, as can be seen in the enlarged sections, both the ecompass and the complementary filters tend to underestimate the true values in the transition phase of the rotation. However, this is compensated by a damping of the operator-induced oscillations, thus satisfying the necessity to reduce as much as possible the fluctuation frequency and their effects on the stability of the measures and of the system in general.

5 Conclusions

In this paper, a preliminary evaluation of different orientation estimation methods based on the use of low-cost sensors is presented. The test is made on data measured by the internal sensors of an iPhone SE (i.e. gyroscope, accelerometer and magnetometer), acquired by the Matlab Mobile application end elaborated with the same software. The registered measurements have been opportunely synchronized and transformed in the coordinates frame required by Matlab to use its built-in integration functions. The experiment has been conducted for two different smartphone settings, aiming at verifying its response during a static acquisition and when subjected to rotations and in general more noisy settings. The data have been integrated using some of the Matlab object filters to give a prior evaluation of this immediate solution; then, a basic Kalman filter algorithm has been structured to integrate the gyroscope measurements with the previously estimated values, to verify if this could enhance the final result. Obviously, the KF needed an opportune tuning process of the measurement and process noise covariance matrix, which in this case has been made following a fuzzy logic-based approach.

Results evidence good performances in both static and dynamic conditions, especially if considering the elementary nature of the experiments specifically targeted at testing easy configurations and solutions.

Further works will be related to a more precise tuning process of the Kalman filter as well as of the Matlab built-in functions, which surely will improve the results.

Moreover, the sensors calibration will be analysed, dealing with their drift and the internal biases of the smartphone, aiming at enhancing the reliability of the estimation. Having said that, these preliminary results can be considered as a good starting point for more elaborated analysis. Orientation estimation stands as one of the key points for an accurate positioning, especially in underwater environments where this not easy task is generally accomplished by the proper integration of different localization systems. INS and acoustic methods already provide optimal results, so the final aim of this study is to lay the foundation for the development of low-cost systems able to provide the same reliability and accuracy of more expensive technology for the orientation estimation as the basis of the overall navigation and localization system.

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