Kalman filter-based yaw angle estimation by fusing inertial and magnetic sensing: a case study using low cost sensors

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Abstract
Purpose – The purpose of this paper is to achieve reliable estimation of yaw angles by fusing data from low-cost inertial and magnetic sensing.
Design/methodology/approach – In this paper, yaw angle is estimated by fusing inertial and magnetic sensing from a digital compass and a gyroscope, respectively. A Kalman filter estimates the error produced by the gyroscope.
Findings – Drift effect produced by the gyroscope is significantly reduced and, at the same time, the system has the ability to react quickly to orientation changes. The system combines the best of each sensor, the stability of the magnetic sensor and the fast response of the inertial sensor.
Research limitations/implications – The system does not present a stable behavior in the presence of large vibrations. Considerable calibration efforts are needed.
Practical implications – Today, most of human–robot interaction technologies need to have the ability to estimate orientation, especially yaw angle, from small-sized and low-cost sensors.
Originality/value – Existing methods for inertial and magnetic sensor fusion are combined to achieve reliable estimation of yaw angle. Experimental tests in a human–robot interaction scenario show the performance of the system.

Keywords Positioning, Sensors, Body sensors

Paper type Case study

1. Introduction

It is of crucial importance for the robotics field, especially for robot autonomy, to have the capacity to estimate orientation of a body in three-dimensional (3D) space. Different approaches have been used in estimating roll and pitch angles, trying to create drift-free solutions (Rehbinder and Hu, 2004). In this context, the yaw angle is more difficult to estimate due to the fact that the gravity measured by accelerometers cannot be used to help to estimate it. Thus, a common solution to estimate yaw angles relies on the fusion of inertial and magnetic sensing. Field *et al.* (2011) present a review on motion capture technologies and current challenges associated to their application in robotic systems. In fact, multi-sensor fusion has been applied in many different ways to improve human–robot interaction (Smits *et al.*, 2006).

In recent years, diverse sensors have become increasingly miniaturized (in size and weight) and cheaper. Inertial sensors (accelerometers and gyroscopes) are no exception. However, only recent advances in micro-electro-mechanical systems (MEMS) have reduced their size and cost considerably, and increased their accuracy. Inertial sensors perform well in motion sensing because they operate regardless of external references, friction, winds, magnetic fields, directions and dimensions. As a drawback, most inertial sensors are temperature-dependent and are not very well-suited for absolute tracking due to error accumulation. On the contrary, they perform better in sensing applications involving relative motion or in the recognition of gesture patterns (Neto *et al.*, 2009). Inertial measurement units (IMUs) consist of a group of inertial sensors that are combined into a unique system with the aim to measure the orientation and position of the unit throughout space and time.

Magnetic sensors, advantageously, allow obtaining an absolute reference for the system in study and do not suffer from the problem of drift that the inertial sensors suffer. A major drawback of magnetic-based sensors is their sensitivity to magnetic distortions in the Earth's magnetic field. Thus, it

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is difficult to acquire reliable readings in the proximity of moving magnetic fields, batteries and ferrous materials.

Other sensors such as optical sensors, ultrasonic sensors and GPS-based systems, have been used for orientation and position estimation. Many tracking systems are based on the combination of different sensor types, hybrid solutions. There are many possibilities to combine individual sensors into a new multi-sensorial system. The positive aspects of different sensors can be explored and combined, originating a "better" sensor. For example, a digital compass, which provides body orientation, can be composed by accelerometers, magnetometers and a temperature sensor. This combination improves the long-term stability and accuracy of data provided by the compass. The small sensors that combine inertial and magnetic sensing are usually called miniature magnetic and inertial measurement units (MIMUs). Some studies combine accelerometers and gyroscopes to achieve reliable orientation data (Foxlin *et al.*, 1998; Kubelka and Reinstein, 2012; Luinge, 2002). The Allan technique can be used in analyzing and modeling the error of inertial sensors (El-Sheimy *et al.*, 2008). An interesting paper presents a complementary filtering algorithm for estimating orientation based on inertial/magnetic sensor measurements (Calusdian *et al.*, 2011). Vlasic *et al.* (2007) use inertial sensors with ultrasonic detection for a practical outdoor capture technique. Kourogi and Kurata (2003) developed a system which estimates poses by integrating data from several sensors attached to a human body using a Kalman filter. In fact, Kalman filter is today extensively used in different applications (Simon, 2001; Welch and Bishop, 1995). Miller *et al.* (2004) report the use of a set of inertial sensors (three sensors) to control the robot arm of NASA Robonaut. Also, GPS-based systems have been used in combination with inertial and magnetic sensors for motion tracking purposes (Sukkarieh *et al.*, 1999; Zhang *et al.*, 2005). A navigation system based on an IMU for walking persons within buildings, where GPS is unavailable, is presented by Ojeda and Borenstein (2007). A system for indoor 3D position tracking recurring to an extended Kalman filter to fuse data from an IMU and a marker-based video-tracking is presented by Hartmann *et al.* (2010). A Kalman filter and particle filtering are implemented on a set of low-cost positioning systems (Khodadadi *et al.*, 2010). A fast converging Kalman filter for sensor fault detection is presented by Jayaram (2010).

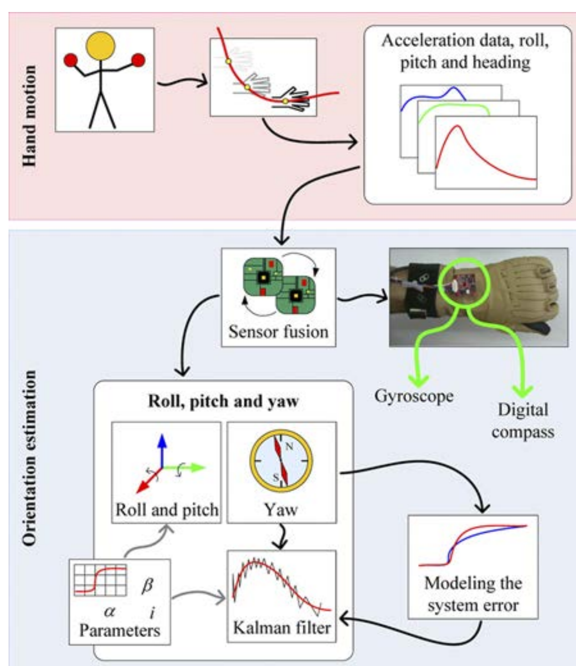
Each different type of sensor has its own advantages and disadvantages. How to effectively integrate/fuse multi-sensor information is the question. Several multi-sensor data fusion methods have been proposed over the years, combining observations from different sensors to achieve "better" descriptions of environments or processes of interest. Error can arise from different factors and situations: misalignment of sensors, calibration, bias, scale factor, thermal drift, unpredictable magnetic fields, etc. Some error sources have a random origin and can only be treated with stochastic processes. To achieve the desired performance, great concern must be paid in relation to all the possible sources of error mentioned above. Jurman *et al.* (2007) present several methods to maximize the performance of an MIMU in terms of calibration and alignment of sensors. An IMU performance has been compared with a Vicon system (Sessa *et al.*, 2012). Other authors approach the problem of motion detection without significant drift (Zhou and Hu, 2007).

1.1 Proposed approach

The method proposed in this paper relies on multi-sensor data fusion (a digital compass and a gyroscope) to obtain more accurate and reliable yaw angle estimations. The digital compass has embedded a 3-axis magnetic sensor (magnetic sensing) and a 3-axis accelerometer (inertial sensing). It provides roll, pitch and heading angles as well as acceleration data. Heading is the angle between the North direction and the direction of the longitudinal axis of the compass in the horizontal plane. Note that heading data can be easily transformed into yaw data by describing the data in relation to a known frame. Digital compasses suffer from some of the weaknesses associated with both magnetic and inertial sensing. It can be reported that, for example, depending on the geographical location and inclination of the compass, a tilt measurement can affect heading accuracy. To achieve more accuracy in yaw estimation, according to previous studies, a Kalman filter can be applied to fuse heading measurements from the compass with integrated angular rates from the gyroscope (Figure 1). A body's angular rate needs to be integrated once to obtain a relative orientation angle, the yaw angle in this scenario. In this context, the gyroscope measures faster changes of orientation (short-term accuracy), thus compensating for the weakness of the compass in this aspect. On the other hand, the compass provides long-term stability of output data. Thus, the individual strength of each sensor is maximized. Roll and pitch angles given by the compass are stable, as they are estimated by fusing data from the magnetometers and accelerometers embedded into the compass.

In summary, the capacity of different low-cost sensors is explored and combined to achieve a major goal, reliable yaw

Figure 1 Layout of the system



angle estimation. Experimental results indicate that the proposed solution is able to eliminate the drift effect produced by gyroscope data and, at the same time, has the capacity to react to fast orientation changes.

2. Yaw estimation

To estimate "more reliable" yaw angles, it is proposed that a Kalman filter be used to fuse heading/yaw data from a digital compass with integrated angular rates from a gyroscope. Thus, the strength of one sensor compensates for the weakness of the other, that is gyroscope data compensate for compass data in case of any disturbances and vice versa. In addition, the gyroscope provides data reporting a faster reaction to rotation. On the other hand, heading/yaw angles from the digital compass contribute to determine an absolute angle and to minimize errors (drift) produced by the gyroscope.

Yaw angles estimated by integrating angular rates from the gyroscope have an error that accumulates with time, so that after a short period, the estimated angles can be totally incorrect. In this way, only short-term accuracy can be achieved using gyroscope measurements. In fact, in this context, gyroscopes are characterized by their short-term accuracy and long-term drift. Yaw angles from the compass ensure long-term stability and reliability. On the contrary, the magnetic sensing characteristics of the compass can lead to distortions in estimated angles.

A body's angular velocity needs to be integrated once to obtain a relative orientation angle (the yaw angle in this case):

$$\psi(t) = \psi_0 + \int \omega(t)\ dt \tag{1}$$

The angular velocity ω sensed by the gyroscope includes components resulting from the Earth's rotation and the sensor motion. However, for the case of the low-cost MEMS with drifts significantly exceeding the magnitudes of the components referred to above, these terms can be omitted. In summary, the gyroscope provides discrete angular rates, $\dot{\psi}_g$, which are numerically integrated to obtain discrete angular increments, $\Delta\psi_g$:

$$\Delta\psi_g(k) = \dot{\psi}_g(k)\ \Delta t \tag{2}$$

These angular increments are added to obtain an estimate to the yaw angle $\psi_g(n)$ at a time t_n:

$$\psi_g(n) = \psi_c(0) + \sum_{k=1}^{n} \Delta\psi_g(k) \tag{3}$$

The initial yaw estimate $\psi_c(0)$ comes from the digital compass, so that $\psi_g(0) = \psi_c(0)$.

2.1 Modeling the system error

Kalman filter models should be simple enough to be implemented and, at the same time, capable to accurately represent the physical scenario in study. Modeling gyroscope errors can be a difficult task because there are different error sources and, usually, it is necessary to decide what are the most important to take into account. The proposed approach is based on previous studies in the field (Brown and Hwang, 1997; Kaniewski and Kazube, 2009; Kaniewski and Kazubek, 2011). Figure 2 shows the proposed solution to estimate yaw angles from gyroscope and compass data. A Kalman filter is used to estimate errors of gyroscope yaw angles, providing such errors to the error updater. The error updater accumulates them and computes the total estimated yaw error $\delta\hat{\psi}_g$, which is subsequently subtracted from the gyroscope yaw angle ψ_g, providing the estimated yaw angle $\hat{\psi}$:

$$\hat{\psi} = \psi_g - \delta\hat{\psi}_g \tag{4}$$

2.2 Kalman filter – implementation

The system in study can be modeled (discrete model) as follows:

$$\mathbf{x}_{k+1} = \mathbf{\Phi}_k\mathbf{x}_k + \mathbf{w}_k \tag{5}$$

Where $\mathbf{x}_{k+1}$ is the process state vector at step $k + 1$, $\mathbf{\Phi}_k$ is the state transition matrix from step k to step $k + 1$, $\mathbf{x}_k$ is the process state vector at step k and $\mathbf{w}_k$ is a vector assumed to be a white sequence with known covariance structure (process noise). The observation/measurement of the process in study is assumed to occur at a discrete time in accordance with:

$$\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k \tag{6}$$

Where $\mathbf{z}_k$ is a measurement vector at step k, $\mathbf{H}_k$ is a measurement matrix and $\mathbf{v}_k$ the measurement error vector.

Error in gyroscope measurements includes scale factor error, bias and Gaussian white noise (Kaniewski and Kazube, 2009). Such errors can be modeled by the following:

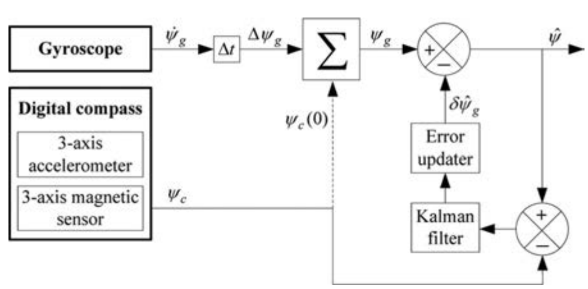
$$\delta\dot{\psi}_g = \delta k\ \ \omega + b + u_\psi \tag{7}$$

$$\delta\dot{k} = u_k \tag{8}$$

$$\dot{b} = u_b \tag{9}$$

Where $\delta\psi_g$ is the yaw error from the gyroscope, δk the scale factor error, b the gyroscope bias and u_ψ, u_k and u_b are the forcing functions, that is Gaussian white noise with power spectral densities S_ψ, S_k and S_b, respectively (Petkov and Slavov, 2010). Gyroscope error models in equations (7), (8) and (9) can be presented in a matrix form:

Figure 2 Estimating yaw angles



$$\frac{d}{dt}\begin{bmatrix}\delta\psi_g \\ \delta k \\ b\end{bmatrix} = \underbrace{\begin{bmatrix}0 & \omega & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0\end{bmatrix}}_{\mathbf{F}}\begin{bmatrix}\delta\psi_g \\ \delta k \\ b\end{bmatrix} + \begin{bmatrix}u_\psi \\ u_k \\ u_b\end{bmatrix} \tag{10}$$

Where the state vector is:

$$\mathbf{x} = \begin{bmatrix}\delta\psi_g & \delta k & b\end{bmatrix}^T \tag{11}$$

In equation (10), we have a linear continuous dynamic model of the system in study, with the following general form:

$$\dot{\mathbf{x}} = \mathbf{F}\,\mathbf{x} + \mathbf{u} \tag{12}$$

Where $\mathbf{F}$ is the fundamental matrix of the system and $\mathbf{u}$ a vector of continuous random process disturbances. This continuous model has to be converted into a discrete model of the system (equation 5) (Brown and Hwang, 1997). The state transition matrix can be determined by:

$$\mathbf{\Phi} = L^{-1}[(s\mathbf{I} - \mathbf{F})^{-1}]_{t=\Delta t} \tag{13}$$

Where $\mathbf{I}$ is the identity matrix and s the Laplace variable. The Gauss–Jordan method is applied to invert the matrix. Applying the inverse Laplace transform to equation (13):

$$\mathbf{\Phi} = \begin{bmatrix}1 & \Delta\psi_g & \Delta t \\ 0 & 1 & 0 \\ 0 & 0 & 1\end{bmatrix} \tag{14}$$

From equations (5), (10) and (14):

$$\begin{bmatrix}\delta\psi_g \\ \delta k \\ b\end{bmatrix}_{k+1} = \begin{bmatrix}1 & \Delta\psi_g & \Delta t \\ 0 & 1 & 0 \\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}\delta\psi_g \\ \delta k \\ b\end{bmatrix}_k + \mathbf{w}_k \tag{15}$$

Now, we need to achieve the covariance matrix $\mathbf{Q}_k$ associated with $\mathbf{w}_k$:

$$\mathbf{Q}_k = E\left[\mathbf{w}_k\mathbf{w}_k^T\right] \tag{16}$$

Where $E[\ldots]$ represents the expected value. The $\mathbf{Q}_k$ elements are calculated using the transfer function method as shown by Kaniewski and Kazube (2009) and Brown and Hwang (1997):

$$\mathbf{Q}_k = \begin{bmatrix}\frac{S_b\,\Delta t^3}{3} + \frac{S_k\,\Delta\psi_g^2\,\Delta t}{3} + S_\psi\,\Delta t & \frac{\Delta\psi_g\,S_k\,\Delta t}{2} & \frac{S_b\,\Delta t^2}{2} \\ \frac{\Delta\psi_g\,S_k\,\Delta t}{2} & S_k\,\Delta t & 0 \\ \frac{S_b\,\Delta t^2}{2} & 0 & S_b\,\Delta t\end{bmatrix} \tag{17}$$

As indicated in Figure 2, the input for the Kalman filter is the difference between the corrected gyroscope yaw $\hat{\psi} = \psi_g - \delta\hat{\psi}_g$ and the yaw angle from the compass ψ_c. This is true assuming that the compass has a zero mean error and the gyroscope presents a considerable drift. Note that the correcting term $\delta\hat{\psi}_g$ is a component of the vector of deterministic inputs $\delta\hat{\mathbf{x}}$. The measurement vector $\mathbf{z}_k$ and the vector of measurement noises $\mathbf{v}_k$ become scalars z and v_c, respectively, so that:

$$\mathbf{H}_k = \begin{bmatrix}1 & 0 & 0\end{bmatrix} \tag{18}$$

It is also necessary to establish the covariance matrix $\mathbf{R}_k$ of measurement noises $\mathbf{v}_k$, which for this system is a scalar, equal to the variance of the compass measurement errors v_c. $\mathbf{R}_k$ can be computed by taking some off-line sampling measurements.

We have now all the parameters necessary to implement the Kalman filter algorithm, Figure 3, in which:

- $\hat{\mathbf{x}}_{k+1|k}$ is the predicted state vector at step $k+1$ (before the measurement update);
- $\hat{\mathbf{x}}_{k+1|k+1}$ is the filtered state vector at step $k+1$ (after the measurement update);
- $\mathbf{P}_{k+1|k}$ is the covariance matrix of prediction errors;
- $\mathbf{P}_{k+1|k+1}$ is the covariance matrix of filtration errors;
- $\mathbf{K}_{k+1}$ is the Kalman gain; and
- $\delta\hat{\mathbf{x}}_k$ is the vector of corrections from the Kalman filter (error updater).

It is necessary to establish an initial value for $\mathbf{P}$, $\mathbf{P}_{0|0}$. If we are absolutely certain that our initial state estimate $\hat{\mathbf{x}}_{0|0}$ is correct, we would let $\mathbf{P}_{0|0} = 0$. However, given the uncertainty in our initial estimate, choosing $\mathbf{P}_{0|0} = 0$ would cause the filter to initially and always believe that $\hat{\mathbf{x}}_k = 0$. Thus, we could choose almost any $\mathbf{P}_{0|0} \neq 0$ and the filter would eventually converge. In this case, we choose $\mathbf{P}_{0|0} = \mathbf{I}$, $\mathbf{I}$ being the identity matrix. This choice for the identity matrix is due to the fact that this initial covariance is considerably higher than the values for which the filter stabilizes after converging. Also, it was verified that this initial value is high enough to not affect the initial convergence velocity.

3. Experiments and results

The experimental evaluation of the proposed platform to estimate yaw angles from the fusion of inertial and magnetic sensing consisted of a set of laboratory tests in which the MIMU is attached to the user's hand. The MIMU motion tracking system is composed of a digital compass (*OceanServer OS500-USA*) and a single-axis gyroscope (*Epson Toyocom XV-3500*). The digital compass is tilt-compensated and contains hard- and soft-iron compensation routines.

Figure 3 Kalman filter loop

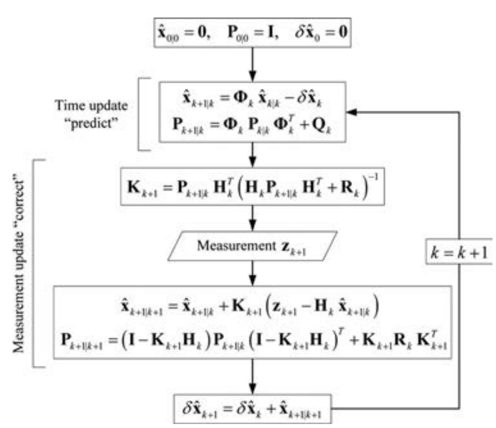
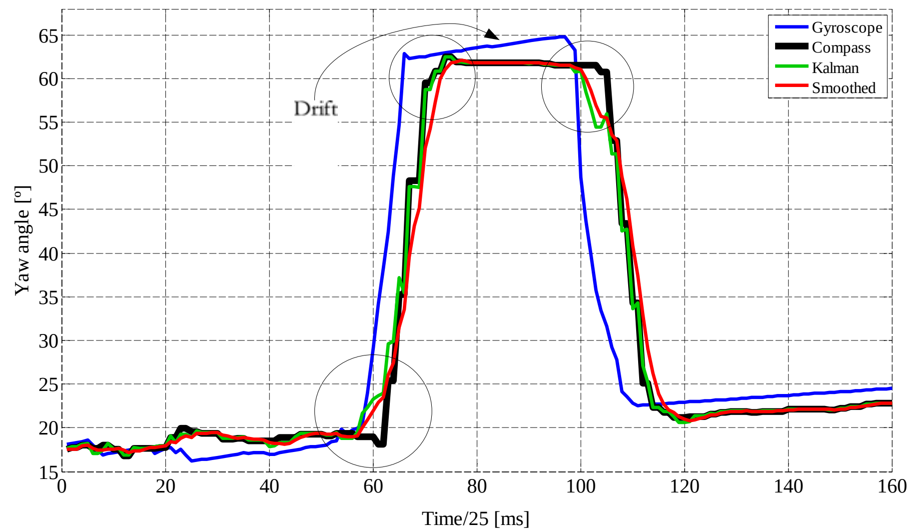


Figure 4 Estimated yaw angles



In a first experiment, the user's hand is oriented to have a yaw angle of about 18°. During this phase, the user causes the hand to vibrate slightly to analyze the system behavior in such conditions. Then, the hand is rotated to an angle of about 62°. There follows a period in which the hand is static and after that the hand is re-orientated for an angle of about 21°. The results presented in Figure 4 contain recordings of yaw angles from the compass, the gyroscope, (when applied) the Kalman filter and a smoothed Kalman filter. The smoothing function is a very simple one, in which for each point provided by the Kalman filter, the average value is computed among its previous three neighbors:

$$x_{i'} = \frac{2x_i + \sum_{j=1}^{3} x_{i-j}}{5} \qquad (19)$$

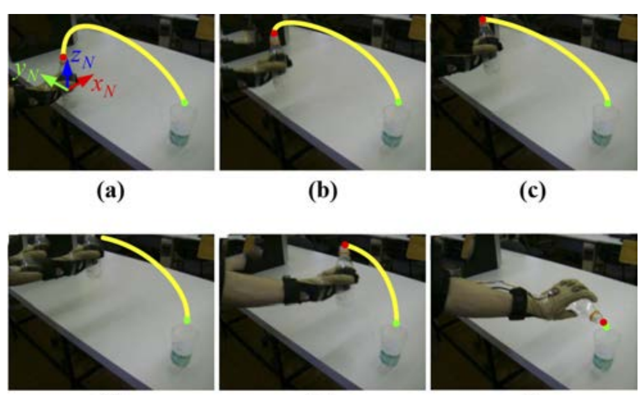
Analyzing the first phase of the experiment (until cycle time 60), the results produced by the Kalman filter and smoothed Kalman filter are stable, in line with the angles provided by the compass. In this phase, it is possible to see the effect of the hand shake. In the end of this initial phase, it is possible to see that the gyroscope reacts faster than the compass to the variation in orientation. In line with the results provided by the gyroscope, the Kalman filter also reacts fast to that change in orientation. This is further evidence that the Kalman filter takes advantage of the positive characteristics of the gyroscope (short-term accuracy) and compass (long-term stability). This aspect can be tremendously important for real-time feedback applications. Between cycle time 60 and 100, the user's hand is static, keeping a yaw angle of about 62°. In this situation, the gyroscope drift is clearly visible (Figure 4). After that, when the user's hand is re-orientated for an angle of about 21°, it is possible to see in Figure 4 that one more time, the Kalman filter helps the system to react fast to the change in orientation. As a final remark, it can be stated that the Kalman filter helps to preserve the fast response of the gyroscope and the long-term stability of the compass, thus eliminating the problem of increasing gyroscope errors.

In a second experiment, the same system was applied in estimating the yaw angle when attached to a human hand performing a pick-and-place operation, that is moving a bottle from one location to another one (Figure 5). Details on the complete system to 3D position and roll and pitch orientation estimation can be seen in the article by Neto *et al.* (2013). Figures 6 and 7 show the results in position and orientation estimation, in which the estimated yaw angle is highlighted with red color.

4. Conclusions and future work

A method for estimating reliable yaw angles from low-cost inertial and magnetic sensors has been described. This method is based on the fusion via a Kalman filter of magnetic and inertial sensing. The Kalman filter allows to preserve the fast response of the gyroscope and the long-term stability of

Figure 5 Setup of the second experiment



Notes: (a) Grasp the plastic bottle; (b) move the plastic bottle in vertical direction and stop for a while; (c) move the bottle along x axis and stop for a while; (d and e) move the bottle in direction to the plastic cup and stop for a while; (f) rotate the bottle to put water in the plastic cup

Figure 6 Estimated 3D poses, view *yx* (*yaw highlighted in red*)

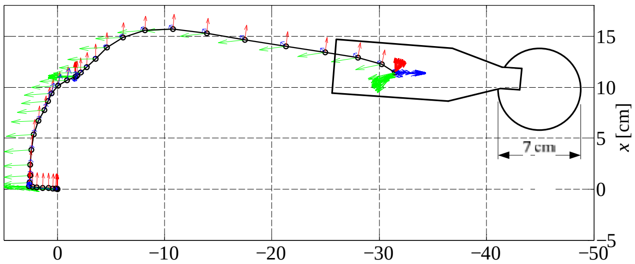
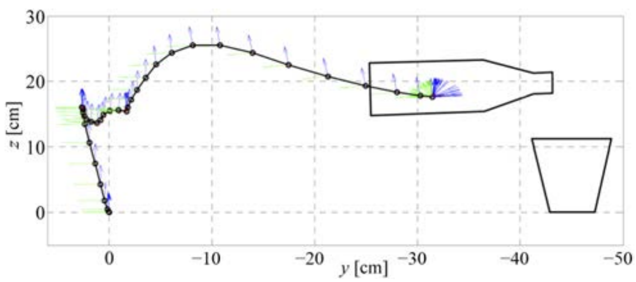


Figure 7 Estimated 3D poses, view *yz* (*yaw highlighted in red*)



the compass, thus eliminating the problem of increasing gyroscope errors (drift). It explores and combines the capacity of different low-cost sensors to achieve a major goal, reliable yaw angle estimation. Experimental results indicate that the proposed solution is able to eliminate the drift effect produced by gyroscope data and, at the same time, has the capacity to react to fast orientation changes.

Future work will focus on reducing the error associated to yaw estimation. One possible solution is the improvement of the hardware that composes the MIMU, namely, in terms of sensitivity and updating rate. In addition, a non-linear filter should be implemented to validate the compass data before entering the Kalman filter.

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