

Sensor fusion system to estimate the trajectory of a low cost mobile robotic platform using an Inertial Measurement Unit

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Abstract.

In this paper, the development and implementation of an algorithm is presented to identify the trajectory of a mobile robot based on data from an Inertial Measurement Unit with nine degrees of freedom consisting of a 3-axis accelerometers, an 3-axis gyroscopes, an 3-axis magnetometers, and an additional temperature sensor to compensate for temperature errors. The combined information from this set of sensors allows determining the trajectory and orientation of the robot at any moment to complement the information from its navigation system. Initially, it was necessary to build controlled test environments that allow observing and getting to know the trajectory and the dimensions thereof for capturing the raw data of the mobile robotic platform. Then, the data obtained from the sensor was processed off-line applying a Kalman filter with the aim to remove Gaussian noise; to estimating the trajectory and the absolute orientation of the mobile robotic platform the proposed algorithm was implemented. This implementation used the hardware elements are inexpensive, thus allowing the necessary testing, the data analysis and the interpretation of the outcome to be replicable and to be used as an educational tool within courses of undergraduate and master level. The elements of hardware used in this implementation are cheap, allowing its reproduction for the analysis and interpretation of data and can be used as an educational tool in courses of undergraduate and master level.

1. Introduction

The miniaturization of electronic devices, including micromachined sensors [1], and the increase in the processing capacity of low-cost embedded systems have allowed the development of new applications by capturing physical information using processing algorithms in the area of sensor fusion [2, 3]. This fusion allows the derivation of information from measures and reduces the estimation error by combining observations or by integrating algorithms. Particularly in recent years, Inertial Measurement Units have been developed, accompanied by sensor fusion techniques to derive all kinds of mechanical variables used nowadays in almost every mobile consumer device to interpret motion variables. One of the areas of further exploration is the monitoring of human activity [4], [5], [6], sports [7], [8], and to assist in the treatment and diagnosis of many diseases [9], [10], [11]. In addition to global positioning systems [3], [12], or simply as absolute guidance system [13], [14]. All these lines of research make it necessary to progress in sensor fusion algorithms and optimization models to deploy applications in simple systems. Furthermore, the



mobile robotic platforms have focused increasingly on daily life applications; it is estimated that in 2013 more than 6 million of those units were in use. Growth in this segment also encouraged the development of an area of research aimed at the design and implementation of navigation systems that enable robots to map the environment and to identify and overcome obstacles to perform their specific task. Until now, most of the operating units derive information about the spatial location and obstacles from encoder signals from the wheels or collisions with objects to complement the inertial measurement system [15], and using Unscented Kalman Filter (UKF) [16], [17]. Although this method has proven effective in domestic applications, it is certain that sensory fusion can optimize currently present problems and eliminate encoders to reduce costs, for this reason we carried out the here described study. In this paper, the development and implementation of an algorithm is presented to identify the trajectory of a mobile robot based on data from an Inertial Measurement Unit with nine degrees of freedom consisting of three accelerometers, three gyroscopes, three magnetometers, and an additional temperature sensor to compensate for temperature errors. The combined information from this set of sensors allows determining the trajectory and orientation of the robot at any moment to complement the information from its navigation system. Initially, it was necessary to build controlled test environments that allow observing and getting to know the trajectory and the dimensions thereof for capturing the raw data of the mobile robotic platform. Subsequently, the data was processed off-line implementing a Kalman filter [18] to remove Gaussian noise from the signal; then the sensor fusion algorithm was implemented allowing estimating the trajectory and the absolute orientation of the mobile robotic platform. It is worth mentioning that all the hardware elements used in the development of this idea are inexpensive, thus allowing the necessary testing, the data analysis and the interpretation of the outcome to be replicable and to be used as an educational tool within courses of undergraduate and master level. Finally, this initiative aims to explore the link between mobile robotics and Inertial Measurement Units to determine the trajectory and the absolute orientation as well as encouraging future studies where this system can be used to detect errors of other typical navigation systems, e.g. to determine the required power according to the inclination of the surface and to detect collisions, among many other applications.

2. Methodology

2.1. IMU MPU9150

The MPU-9150 is an integration of three sensors: 3-axis gyroscope, 3-axis accelerometer and 3-axis magnetometer. The gyroscope has a operating ranges of ± 250 , ± 500 , ± 100 and ± 2000 dps. The accelerometer has a programmable range of ± 2 , ± 4 , ± 8 and ± 16 g. The power range of the circuit is 2.4v - 3.46 v.

2.2. 1D Kalman Filter

The output signal of the accelerometer has a high noise component that can be characterized as Gaussian noise. Therefore, it was necessary to implement a 1D Kalman filter. The equations are shown in Equation 1 where \hat{X}_k is the estimated value, Z_k is the measured value and K_k is the Kalman gain.

$$\hat{X}_k = K_k Z_k + (1 - K_k) \hat{X}_{k-1} \quad (1)$$

To calculate K_k it is necessary to know or to estimate the error covariance of the process P , the error covariance of the observation R that in the case of the accelerometers can be obtained with the probability density function of the data while the accelerometer is static. If the value of R is known, the process shown in Equation 2 will be used, where m is a vector of previously acquired raw samples to obtain the nature of the noise. Note that in this case, since the application of the filter in a one-dimensional signal is scaled, the matrix $A = 1$, and the deviation Q should be adjusted to the speed of the system.

$$\begin{aligned}
 K_k &= \frac{P_k}{P_k + R} \\
 \hat{X}_k &= \hat{X}_{k-1} + K_k(Z_k - \hat{X}_{k-1}) \\
 P_k &= (1 - K_k) P_{k-1} \\
 \text{Where, } X_{(0)} &= \text{mean}(m); P_{(0)} = \text{mean}(m); R = \sigma^2(m)
 \end{aligned} \tag{2}$$

2.3. Orientation and magnitude

After applying the calibration procedures [18], and implement 1D Kalman filter, model described in Equation 3 can be applied to estimate the trajectory of the mobile platform. Importantly calibration algorithms are essential to the correct functioning of this model [18].

$$\begin{aligned}
 \text{Orientation} &= \tan^{-1} \left(\frac{mc_y}{mc_x} \right) \\
 \text{Magnitude} &= \sqrt{ac_x^2 + ac_y^2}
 \end{aligned} \tag{3}$$

2.4. Reference system test

To develop the model, it is necessary to have a reference system. For this purpose we used a line follower, which moves in geometric figures. The figures were printed on white paper with black ink. Twelve basic geometric figures were taken, three squares, three circles, three rectangles and three ovals. The dimensions of the squares are, 15 cm, 25 cm and 35 cm respectively, those of the circles are 13 cm, 23 cm and 33 cm of radius; for the rectangle the dimensions are 36 cm 25 cm, 35 cm 26 cm and 20 cm 31 cm, and finally the ovals dimensions are 49 cm 33 cm, 34.5 cm 23 cm and 18.5 cm 13 cm. By using a line follower robot, a route of three full circulations was performed of each figure, and data was collected with an Inertial Measurement Unit (IMU), reference IMU9150, which records 9 degrees of freedom. This data was used as training data and validation.

3. Results

To apply the linear Kalman filter, it must be absolutely assured that the nature of the noise is Gaussian. Figure 1 shows the PDF of the static signal of IMU9150 on the x-, y- and z-axis (accelerometer) before and after applying the Kalman filter. These results were obtained by placing the accelerometer on an anti-vibration table with a sampling frequency of 150 Hz.

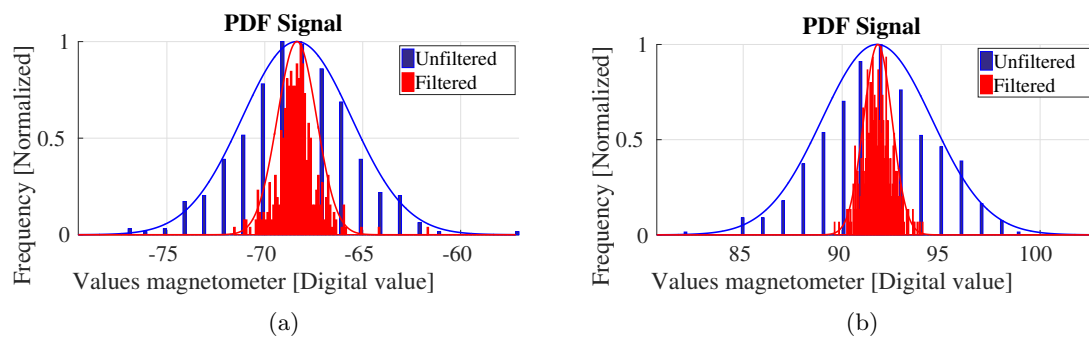


Figure 1. (a) Kalman filter m_x (b) Kalman filter m_y

Figure 2 shows the evolution of orientation and reconstruction of the trajectory using the oval. As shown, four cycles were completed. Accumulation of bias is the difference in paths.

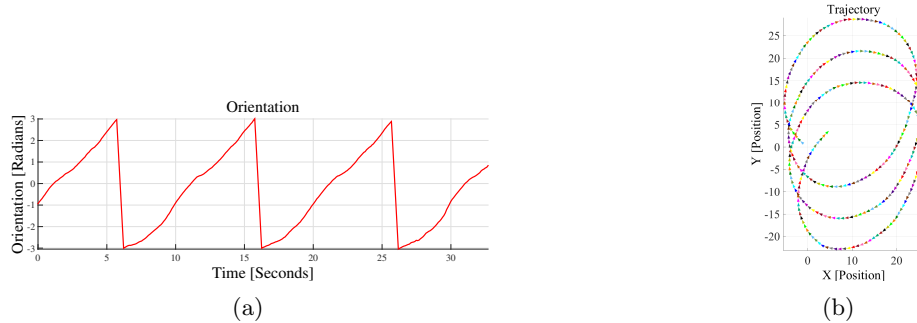


Figure 2. (a) Oval orientation (b) Oval path

Figure 3 shows the rectangular tracking path. It is clear that the corners are not defined, but this effect is in the way the mobile platform monitors the line in the reference system.

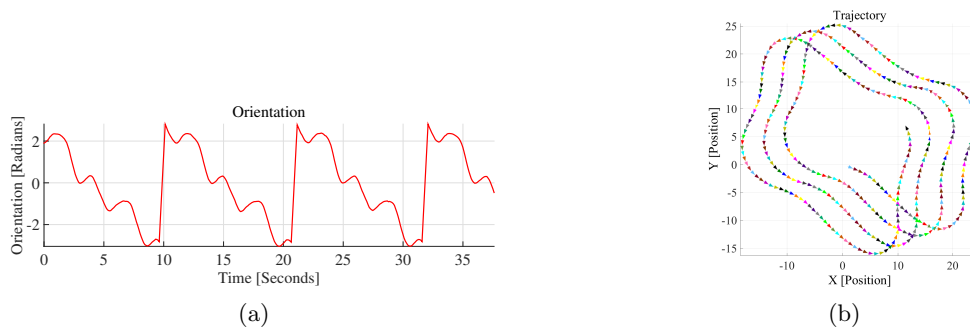


Figure 3. (a) Rectangle orientation (b) Rectangle path

Finally in Figure 4, shown the path tracking by dynamic bias correction adjusting it with the temperature value. Clearly, the center of the road moves less than in previous experiments.

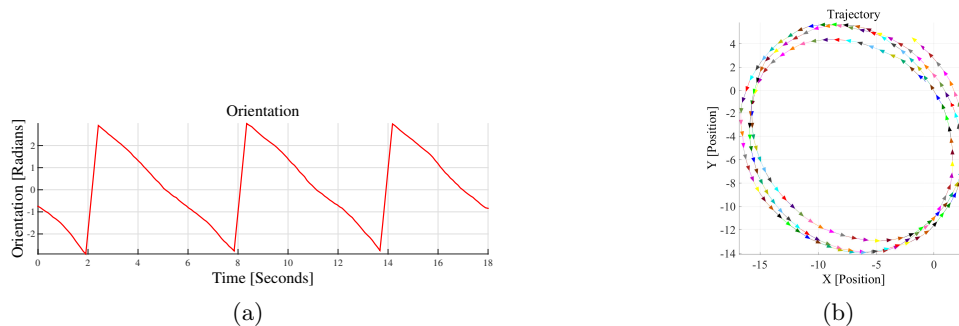


Figure 4. (a) Circle orientation (b) Circle path

4. Conclusions

In this paper a model to approximate the path of a mobile robot is presented using data from a magnetometer and a gyroscope; and further to approximate the size of the path with the values of the accelerometer. This work is presented as a first approximation to a model that allows for absolute tracking of a mobile robot. Testing the implementation of a 1D Kalman filter was performed for each of the three accelerometer measures and their effectiveness was shown. Importantly, the models effectiveness depends heavily on the quality of the measured signal. Finally, the approach shown in this article allows demonstrating the utility of the Inertial Measurement Units for kinematic models. Advances in this area are adaptable to the applications mentioned above such as sports, the analysis of human activity and the treatment and diagnosis of diseases.

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