Improved Position Estimation of Real Time Integrated Low-Cost Navigation System Using Unscented Kalman Filter

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Abstract. Low cost Micro Electrical Mechanical Systems (MEMS) inertial sensors have nominated their use in domains such as navigation systems but these sensors are noisy and characterized by their measurements drift and large errors. In this work, an integrated navigation system is implemented and its performance is evaluated through experimental work in both post processing and real time domains. The real time processing is built on multi-platform 32-bit ARM core ATMEL microcontroller while at the same time raw sensors measurements are saved for post processing under MATLAB. North and East position errors measurements were used in this work to evaluate position improvement calculated using MEMS inertial sensors integrated with position and velocity from Global Positioning System (GPS) receiver readings at slow rates. For such evaluation, the calibrated measurements from gyroscopes and accelerometers are fed to a mechanization process to build an inertial navigation system (INS). The INS drifting navigation solution is fused with a GPS measurement through Unscented Kalman Filter (UKF). UKF does not require linearization of the system model such as the status of the commonly used Extended Kalman Filter (EKF). The results of the experimental work show that the implemented low cost integrated navigation system based on UKF can achieve a level of accuracy superior than other (EKF) based expensive systems.

1. Introduction

Recently, the use of MEMS has spread in many areas such as navigation systems used in the unmanned aerial vehicles, submarines and land vehicles because of its low weight, low cost and low power consumption compared with the previous systems which are characterized by their size, high cost and high consumption of energy. Some problems related to MEMS usage is the deviation of the accuracy of the readings over time [5-12]. To obtain a true prediction of navigational information, the MEMS accuracy problems must be compromised for further processing to convert the observations to useful data for accurate attitude and position estimation. The selected IMU sensor’s assembly used in this work is MPU-6050 from InvenSense® [6]. This IMU combines three-axis gyroscopes (gyros), three-axis accelerometers. A microcontroller board based on a 32 bit ARM core processor and 512 KB memory was used to execute navigation arithmetic calculations [7]. The mechanization model was supplied by calibrated data, which offers continuous navigation information (attitude, velocity and position) of the vehicle. The Global Positioning System (GPS) provides a more accurate and continuous positioning, but needs a direct line of sight for not less than four satellites to solve the
position equations [14]. However, GPS accuracy depends on the availability of GPS satellites and affected by jamming. Compared with GPS, INS has the advantage of being unaffected by jamming and depends on itself without external information, such as radio signal. However, using INS alone leads to a deviation of the path due to the integration of errors in the inertial sensors therefore, GPS and INS are often integrated together to improve the accuracy [11-12] and redundancy. With the continuous development of navigation technology, higher requirements for accuracy, size and reliability of navigation systems were needed. Improving the accuracy of INS and enhancing inertial instrumentation accuracy would result in a sharp increase in cost, so research in this area became a very important focus. Typical solution to fuse GPS and INS measurements is to use the extended Kalman filter (EKF). However, EKF is built on basic assumptions of a linear system and Gaussian noise distribution. Thus, the INS 1st order linearized error model is usually used. Although this assumptions have proved a very good performance, but the usage of EKF on a real time system requires a superior performance processing platforms to solve for the EKF equations which include the multiplication and inversion of minimum of 9x9 and up to 22x22 matrices [2]. Unlike EKF unscented Kalman filter (UKF) doesn’t require a linear model but can be applied directly to the nonlinear model. At the same time UKF doesn’t require a massive mathematical operation and can be applied on a medium performance micro controller [15-16]. The objective of this work is to evaluate and validate the performance enhancement of the position estimation, by implementing a low cost integrated navigation system based on a selected low-cost MEMS inertial sensor and a low cost commercial GPS receiver connected together on two 32-bit ARM core microcontroller boards. The mechanization process and the UKF processes are performed on one of the microcontroller boards which is connected to the IMU, while the other board is dedicated for the GPS data synchronization. The IMU and GPS raw measurements are logged for further post processing under MATLAB for system tuning and offline integration evaluation that helps in upgrade of the sensor performance. In the next section, the mechanization model block diagram in local level frame is presented. Section (3) describes the Unscented Kalman Filter theory, while section (4) presents the GPS/INS system implementation using UKF. Section (5) the experimental work and results. Finally, the conclusion is presented in section (6).

2. Mechanization Model in Navigation Frame

Mechanization is a technique for finding the speed, position and attitude of the vehicle, in the navigation frame, east, north and up (ENU), from the data of the IMU outputs, which are the rotation rates measured from three gyros and specific forces measured from three accelerometers, these data are relative to the inertial frame as, shown in Figure 1 [1-9].

Figure 1. Mechanization diagram of an INS in the local level frame (after [4])
The acceleration was measured by the accelerometers in the body frame, and then it transformed to navigation frame for getting useful information. This operation had done using transformation matrix through the attitude angles that obtained from integrating the gyro rates. The projected accelerations had purified from Coriolis motion and the external effects of gravity for getting pure implication of the body motion. The output was integrated to obtain position and velocity as described in [1,9].

3. Unscented Kalman Filter
For the EKF, Gaussian distribution is assumed to approximately distribute the states, hence it is propagated analytically to linearize the nonlinear system to by linearization of first order form. Linearization may introduce high value of errors in the true next mean and covariance of the Gaussian random variable (GRV) that has been transformed, and then may lead to not good performance and also filter divergence. The UKF solves above problem by using deterministic approach of sampling. The state is approximately distributed again by a GRV, but through using a minimal set sample points chosen carefully. The sample points capture completely the true mean and covariance of the GRV, and when they are propagated through the nonlinear system, they capture the next mean and covariance accurately to the third order (expansion of Taylor series) applied to any nonlinearity.

3.1. Unscented Transformation
The unscented transformation (UT) is a technique for determining the statistics of random variable that has a nonlinear transformation. Consider propagation a random variable \( x \) (dimension \( L \)) through a nonlinear function, \( y = f(x) \). Assume \( x \) has mean \( \mu \) and covariance \( P_x \). To calculate the statistics of \( y \), we form a matrix \( \chi \) of \( 2L + 1 \) sigma vectors

\[
\chi_0 = \mu, \\
\chi_i = \mu + (\sqrt{(L+\lambda)P_x})_i, \quad i = 1, ..., L, \\
\chi_i = \mu - (\sqrt{(L+\lambda)P_x})_{i-L}, \quad i = L + 1, ..., 2L. 
\]

\( \chi_i \) according to the following

where, \( \lambda = \alpha^2 (L + k) - L \) is a parameter of scaling. \( \alpha \) determines the spread of the sigma points around \( \mu \), and is small positive value (e.g., \( 1 \leq \alpha \leq 10^{-4} \)). The constant \( k \) is a secondary scaling parameter, which is usually set to \( 3 - L \), and \( \beta \) is used to incorporate prior knowledge of the distribution of \( x \) (for Gaussian distributions, \( \beta = 2 \) is optimal). \( (\sqrt{(L+\lambda)P_x})_i \) is the \( i \)-th column of the matrix square root (e.g., lower-triangular Cholesky factorization). These sigma vectors are propagated through the nonlinear function;

\[
Y_i = f(\chi_i), \quad i = 0, ..., 2L. 
\]

The mean and covariance for \( y \) are approximated using a weighted sample mean and covariance of the posterior sigma points,

\[
\mu_y \approx \sum_{i=0}^{2L} W_i^{(m)} Y_i, \\
P_{yy} \approx \sum_{i=0}^{2L} W_i^{(C)} (Y_i - \mu_y)(Y_i - \mu_y)^T, 
\]

where

\[
W_i^{(m)} = \frac{1}{2L+1}, \\
W_i^{(C)} = \frac{\beta}{\sqrt{2L+1}} \frac{1}{\sqrt{\lambda+\alpha^2 L}} (\sqrt{(L+\lambda)P_x})_i 
\]
with weights $W_i$ given by

$$W_0^{(m)} = \frac{\lambda}{L + \lambda}, \quad W_0^{(C)} = \frac{\lambda}{L + \lambda} + 1 - \frac{\alpha^2}{2} + \beta, \quad W_i^{(m)} = W_i^{(C)} = \frac{\lambda}{2(L + \lambda)}, \quad i = 1, \ldots, 2L. \quad (5)$$

![Image of Figure 2]

**Figure 2.** gives an example of a 2-system. In figure 2a, the mean and covariance have been propagated by Monte-Carlo sampling, in figure 2b, the output by linearization method like (EKF) and figure 2c, the output of UT method by using 5 sigma points. The posterior performance of UT is clear.

### 3.2. Unscented Kalman filter Implementation

The UKF can be implemented using UT method by expanding the state space to include the noise component: 

$$\hat{\chi}_k^a = \begin{bmatrix} \hat{x}_k^T & \omega_k^T & v_k^T \end{bmatrix}^T. \quad \text{The UKF can be summarized as follows [13], [17].}$$

**Initialization parameters**

$$\hat{x}_0 = E[x_0], \quad P_{x_0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]$$

$$\hat{x}_0^a = E[x_0^a] = \begin{bmatrix} \hat{x}_0^T & 0 & 0 \end{bmatrix}^T$$

$$P_0^a = E[(x_0^a - \hat{x}_0^a)(x_0^a - \hat{x}_0^a)^T] = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & R_v & 0 \\ 0 & 0 & R_n \end{bmatrix} \quad (8)$$

For $k = 1, \ldots, \infty$

1. $t = k - 1$

2. **Sigma Points**

$$\chi_i^a = \left[ \begin{array}{c} \chi_i^a \hat{x}_i^a \\ \gamma \sqrt{P_i^a} \end{array} \right] \chi_i^a - \gamma \sqrt{P_i^a} \chi_i^a$$

3. **The time update equations** are:

**Propagation of the sigma points through the system equation**

$$\chi_{k,t} = f(\chi_t^x, \chi_t^v, u_t)$$

$$\hat{x}_k = \sum_{i=0}^{2L} \omega_i^m \chi_{i,k}^x \quad (11)$$
\[
P_{x_k} = \sum_{i=0}^{2L} \omega_i^c (\chi_{i,k}^x - \hat{x}_k^-)(\chi_{i,k}^x - \hat{x}_k^-)^T + R_v
\]  
\(12\)

The augmented sigma points is
\[
\chi_{k,t} = [\hat{x}_k^- \hat{x}_k^- + \gamma \sqrt{P_{x_k}^-} \hat{x}_k^- - \gamma P_{x_k}^-]
\]  
\(13\)

4. Filtering
\[
Y_{k,\beta} = h(\chi_{i,k,\beta})
\]  
\(14\)

\[
\hat{y}_k = \sum_{i=0}^{2L} \omega_i^m Y_{i,k,\beta}
\]  
\(15\)

\[
P_{y_k} = \sum_{i=0}^{2L} \omega_i^c (Y_{i,k,\beta} - \hat{y}_k^-)(Y_{i,k,\beta} - \hat{y}_k^-)^T
\]  
\(16\)

\[
P_{x_k,y_k} = \sum_{i=0}^{2L} \omega_i^c (\chi_{i,k,\beta}^x - \hat{x}_k^-)(Y_{i,k,\beta} - \hat{y}_k^-)^T + R_n
\]  
\(17\)

\[
K_k = P_{x_k,y_k} P_{y_k}^{-1}
\]  
\(18\)

\[
\hat{x}_k = \hat{x}_k^- + K_k (y_k - \hat{y}_k^-)
\]  
\(19\)

\[
P_{x_k} = P_{x_k}^- - K_{k} P_{y_k} K_{k}^T
\]  
\(20\)

where
\[
\gamma = \sqrt{L+\lambda}, \omega_0^m = \frac{\lambda}{L+\lambda},
\]
\[
\omega_0^c = \omega_0^m + (1 - \alpha^2 + \beta), \omega_i^c = \omega_i^m = \frac{1}{2(L+\lambda)}
\]

\[1 \leq 3 < \alpha < 1, \beta = 2, k = 0\]

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**Figure 3.** Operation of the unscented Kalman filter.

Figure 3, described the UKF steps, firstly sigma points are generated from initial mean and covariance, secondly the sigma points are transferred through the dynamic system. As a third step, mean and covariance of the transformed sigma points are captured. Fourthly, augmented sigma points from the captured mean and covariance are calculated. Finally, the measurement and their mean and covariance are calculated and the Kalman gain, state and covariance are updated.
4. GPS/INS Integrated System Implementation

GPS and INS operate independently. INS provides separate navigation solution (position, velocity and attitude) with errors increased rapidly with time. To improve this solution the position and velocity from GPS is fed to UKF filter as observer measurements to obtain corrected state estimation which is feed back to the INS navigation, as shown in Figure 4.

![Diagram](image)

**Figure 4.** GPS/INS system implementation diagram.

4.1. Hardware configuration

The used hardware consists of two 32-bit ARM core microcontroller boards, one is a master where it collect directly the raw data from IMU MPU6050 [6] and perform mechanization calculation of state estimation, the second board collect the data from GPS SKM53 [7] receiver module and send it through serial port to the master one with interrupt every 1 sec update. The master one receives the GPS data and performs the UKF integration calculation to correct the navigation states. The corrected navigation states are sent through COM port to a logging PC to be analyzed later. Figure 5 illustrates the connection diagram and a photo of the used hardware.

![Photos](image)

**Figure 5.** Hardware configuration  
**Figure 6.** Reference trajectory

4.2. Test environment

A vehicle-navigation test was carried out in fifth settlement near the ring road – New Cairo. The raw data from IMU and GPS measurement were collected at 40Hz and 1Hz, respectively. A typical number of about 7~10 visible satellites with car velocity 50 km in average was the test environment. Figure. 6 shows the reference trajectory of the experiment relative to GPS data. The total navigation time is 294 sec. The first 50 sec was a stopping period for initial alignment, after that the car had travelled for 264 sec.
5. Experimental Work and Results

5.1 Navigation results during GPS 1 sec update rate

The performance of INS integration system is improved after being integrated with GPS, in terms of the quantitative position errors such as, the mean, standard deviation, maximum error. The maximum horizontal error (MHE) is calculated after integration as shown in Table 1 and Figure 7. In Figure 8, the velocity components in East, North and Up directions are depicted. It is clear that there is reduction in errors after using UKF. Figure 9 shows the navigation resultant trajectory in Latitude/Longitude, and Figure 10 represents the total velocity relative to GPS reference velocity, it found that the results follow the reference with a significant errors.

| Table 1. Position errors during navigation in case of 1 sec. GPS update rate |
|---|---|---|---|
| Mean | Std. | Max. Error | Max. horizontal error (m) |
| East | 0.3638 | 0.461 | 3.797 | 4.7 |
| North | 0.4594 | 0.453 | 2.788 | |

Figure 7. Position errors in East/North for GPS/INS integrated system

Figure 8. Velocity in East, North and Up for GPS/INS integrated system

Figure 9. Lat./Lon. for GPS/INS integrated system

Figure 10. Total velocity for GPS/INS and GPS reference velocity
5.2 Navigation results during 10 sec GPS outage

In this section, a 10 sec GPS data outage is presented which simulate a tunnel crossing or an urban canyon. The accumulated INS position error increases rapidly during outage interval. After that, the UKF integrates back GPS with INS data to dramatically damp the position error as shown in Figures 11 to 14.

In Table 1, the quantitative position errors such as, the mean, standard deviation, maximum error is presented. The (MHE) is calculated to be equal to 126.89 m during a 10 sec GPS outage.

|        | Mean   | Std.  | Max. Error | Max. horizontal error (m) |
|--------|--------|-------|------------|--------------------------|
| East   | 1.625  | 8.694 | 102.5      |                          |
| North  | 1.438  | 6.586 | 74.8       | 126.89                   |

**Table 2. Position errors during navigation in case of 10 sec. GPS outage**

**Figure 11.** Position errors in East/North for GPS/INS integrated system

**Figure 12.** Velocity in East, North and Up for GPS/INS integrated system

**Figure 13.** Navigation result in Lat/Lon for GPS/INS integrated system

**Figure 14.** Total velocity for GPS/INS and GPS reference velocity
6. Conclusion
The work submitted in this paper presented INS/GPS integration of a low cost based integrated navigation system, which consists of MEMS IMU and commercial global positioning system (GPS) based on loosely coupled integration implemented on a 32-bit ARM core microcontroller using UKF to estimate and improve the navigation state parameters represented in ENU frame with respect to earth. The results of real trip show the performance of the UKF on the inertial navigation nonlinearity without the need of linearization of state model. The results showed that UKF estimates the navigation states accurately in presence of GPS signals, but during the GPS outage the estimated navigation errors were degrading rapidly because of errors of inertial sensors which had not been estimated. Finally the paper showed that the microcontroller core can handle the computational complexity of performing the unscented transformation process of the proposed UKF with good navigation states results compared with the reference trajectory.

References
[1] Aggarwal P 2010 MEMS-based Integrated Navigation GNSS technology and applications Artech House.
[2] El-Sheimy N 2007 ENGO 623 Lecture notes: Inertial Techniques and INS/DGPS Integration Calgary University.
[3] ElDesoky A, Kamel A, Elhabiby M and Elhennawy H 2017 Performance Enhancement of Low-Cost MEMS Inertial Sensors Using Extensive Calibration Technique 34th National Radio Science Conference.
[4] Hassabla A and Kamel A 2015 Estimation Techniques for Low-Cost Inertial Navigation Systems Msc. Military Technical College.
[5] KVH 2014 Guide to Comparing Gyro and IMU Technologies MEMS and FOGs Industries Inc.
[6] MPU-6050 Product Specification https://www.invensense.com/products/motion-tracking/6-axis/mpu-6050.
[7] Due microcontroller product Specification https://components101.com/microcontrollers/arduino-due
[8] Haykin S 2001 Kalman Filtering and Neural Networks John Wiley & Sons, Inc.
[9] Noureldin A, Karamat T B and Georgy J Fundamentals of Inertial Navigation, Satellite-based Positioning and their Integration Springer.
[10] Robin L and Perlmutter W 2011 IMU High Performance Inertial MEMS Yole Development France
[11] Shin E H 2005 Estimation Techniques for Low Cost Inertial Navigation PHD in Geomatics Engineering Calgary.
[12] Sofian M, Hazry D and Zul A 2009 Study of Inertial Measurement Unit Sensor the International Conference on Man-Machine Systems (ICoMMS).
[13] Julier S and Uhlmann J K 1997 A new extension of the Kalman filter to nonlinear system The 11th International Symposium on Aerospace/Defense Sensing, Simulation and Controls, Multi Sensor Fusion, Tracking and Resourse Management II, SPIE.
[14] Zhang P, Evangelos G and Milios E 2005 Navigation with IMU/GPS Digital Compass with Unscented Kalman Filter International Conference on Mechatronics & Automation, Niagara Falls, Canada.
[15] Xuhua Z, Fengjun Q and Hongtao Z 2012 Application of Unscented Kalman Filter in GPS/INS Symposium of Photonics and Optoelectronics.
[16] Aftatah M, Lahrech A and Abounada A 2016 GPS/INS/Odometer Data Fusion for Land Vehicle Localization in GPS Denied Environment Modern Applied Science.
[17] Wan E A and van der Merwe R 2000 The unscented Kalman filter for nonlinear estimation Adaptive Systems for Signal Processing, Communication and Control, IEEE Press, Lake Louise, Canada.