INS/GPS Integration System for Low Cost MEMS

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Abstract: Navigation systems are constantly demanding for exploding system performance and minimizing system size. They require higher accuracy, reliability, robustness against jamming, impossibility to intercept and ability to fit very small compartments. Low-cost inertial sensors are described by high noise and large doubts in the outputs such as bias, scale factor, drift and non-orthogonality. So, errors associated with a low-cost microelectromechanical systems (MEMS) in terms of position, velocity and attitude grow rapidly in standalone mode. If decent performance can be reached with low-cost inertial measurement unit (IMU), the cost of real applications can be reduced and the growth of new applications may be made feasible. The technique to advance the accuracy is supplementing the IMU with some aiding sources; for example, global positioning system (GPS) or digital compass. This motivates the system-integrators to enhance the performance by integrating the long-term GPS accuracy with the short-term INS accuracy.

Key-Words: IMU, INS, GPS, Kalman filters; navigation states.

1 Introduction

An inertial navigation system (INS) provides information about position, velocity, and attitude based on the measurement gyroscopes and accelerometers which consequently measure the rotation rates and the specific forces. It's a Dead Reckoning (DR) system, which means that it doesn't need any external references and defined as the process of calculating the current position of a vehicle by the knowledge of previous position, distance travelled and measurement direction of motion. Inertial Navigation System is an integrated system, mainly composed of an inertial measurement unit (IMU) and signal processing module. The combination of sensors measurements is used to determine all the navigation states using a signal processing which handle the model computations and integrations. An IMU consists of three of accelerometers combined together in an orthogonal arrangement and three gyroscopes arranged in the same manner as accelerometers. These sensors are jointly processed to obtain a full state estimation of the body [1]. The accuracy of obtaining the navigation states of the body depends on the grade of the IMU, such as tactical grade, navigation grade which their measurements can be used directly by strapdown inertial system algorithm due to their high accuracy but they are very expensive [2,3]. On the other hand, low-cost grade IMU which has the advantage of small size, light weight and low price suffers from high noise that causes the INS to deliver kilometre level positioning errors in just few seconds [4]. If these errors are minimized, then the navigation states drift of inertial system will be minimized. In the past few years, huge developments have been achieved in the field of low-cost sensors error estimation. These achievements have contributed in the industry of inertial sensors navigation system and made it possible to obtain low cost and accurate system at the same time. This can be clearly seen in the market of low-cost inertial sensors where huge companies can buy the processing techniques and knowhow of error estimation by tens of millions of dollars [5]. INS play a major role for various moving/flying platforms. It is corner stone for guidance and control system for both civilian and military applications. Inertial sensor assembly (ISA) is among the important components that constitute the various types of seeker tracking systems for terminal guidance phases, autonomous land vehicles, unmanned aerial vehicles, submarines and torpedoes which get benefits of such INS accuracy enhancement. This thesis focuses on error estimation techniques to enhance the low-cost inertial navigation systems. inertial sensors errors. Kalman filter is an algorithm for optimally estimating the error states of a system from measurements contaminated by noise. This is a sequential recursive algorithm that provides an optimal least mean variance estimation of the error states. The objective of this research work is to enhance the performance of a low-cost MEMS based INS. To reach this goal, typical and deeply investigated estimation algorithms are introduced. These algorithms deal with different types of inertial sensors errors such as deterministic and stochastic errors. Deterministic errors are usually compensated through calibration process. For this purpose, an extensive work has to be done under this topic. On other hand, stochastic errors are hard to predict and cause the main difference between cheap and expensive sensors. An accurate error estimation technique has to be designed to raise the accuracy level of low-cost sensors to reach a level that enables it to be used with applications that require accurate and cheap navigation systems. To test the designed algorithms, they have to be implemented on a real time system that can be used in field experiments under different conditions. To achieve this goal, the procedure of hardware selection has to be well accomplished. Moreover, system integration and real time code implementation have to be neatly organized. The software process phase will include the development of software algorithms to communicate with the selected IMU and store the sampled data, integration and testing of the whole system using real-world data, estimation filter tuning, and finally the implementation of the algorithms in C++ for the use in a real-time system. Inertial sensors continuously calculate the position, velocity, and orientation of a moving object without the need for external references. These range from mechanical and optics which are extremely accurate, down to low cost inertial sensors which are not accurate enough to be used in highly sensitive applications. Typical applications for sensor systems vary from type to type according to various grades of sensors such as, control and stabilization, navigation and correction, pedestrian navigation, head trackers, and mobile mapping. Given specified initial conditions, one integration of acceleration provides velocity and a second integration gives position. Angular rates are processed to give the attitude of the moving platform in terms of pitch, roll and yaw, and also to transform navigation parameters from the body frame to the local-level frame [6]. The global positioning system (GPS) was developed by the US Department of Defence in the early 1970s to serve military navigational requirements. The first satellite was launched in 1978 and the system was declared operational in 1995. It is based on a network of at least 24 satellites (with room for six further satellites) orbiting the Earth in nearly circular orbits with a mean radius of about 26,560 km [1]. It calculates the satellite's position from the information in the navigation message. With the information from at least three satellites the receiver can use the process of trilateration to calculate its own position in terms of latitude, longitude and altitude. The signal from a fourth satellite is needed to cancel the receiver's clock bias.

2 Estimation Technique for sensors integration

The mechanization algorithm in the l-frame provides the position in curvilinear coordinates as latitude, longitude and latitude (λ, φ, h), the velocities along the east, north and up directions (V_E, V_N, V_U) and the attitude angles as a familiar pitch, roll and yaw (p, r, y). Obtain rotation rates from the gyroscopes ($\omega_x, \omega_y, \omega_z$) which are measured in (rad/sec) and specific forces from accelerometers (f_x, f_y, f_z) which are measured in (m/sec^2). These measurements are considered to be the raw data of the IMU resolved in the body frame.

2.1 Error state equation

The error state vector for the mechanization equations in the local-level frame consists of the errors along the curvilinear geodetic coordinates (latitude error$\delta\varphi$, longitude error δλ, altitude error δh) as follow [8]

$$\delta\dot{r}^l = \begin{bmatrix} \delta\dot{\varphi} \\ \delta\dot{\lambda} \\ \delta\dot{h} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{M+h} & 0 \\ \frac{1}{(N+h)\cos\varphi} & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \delta V^e \\ \delta V^n \\ \delta V^u \end{bmatrix} \tag{1}$$

The errors along the earth-referenced velocities (east component error δV^e, north component error δV^n, up component error δV^u) as follow

$$\delta\dot{V}^l = \begin{bmatrix} \delta\dot{V}^e \\ \delta\dot{V}^n \\ \delta\dot{V}^u \end{bmatrix} = \begin{bmatrix} 0 & f^u & -f^n \\ -f^u & 0 & f^e \\ f^n & -f^e & 0 \end{bmatrix} \begin{bmatrix} \delta p \\ \delta r \\ \delta A \end{bmatrix} + R_b^l \begin{bmatrix} \delta f^x \\ \delta f^y \\ \delta f^z \end{bmatrix} \tag{2}$$

Where p is the pitch angle, r is the roll angle and A is the azimuth angle. The errors along the three attitude angles (pitch errorδp, roll error δr, azimuth error δA) as follow

$$\dot{\Psi}^l = \begin{bmatrix} \delta\dot{p} \\ \delta\dot{r} \\ \delta\dot{A} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{M+h} & 0 \\ \frac{-1}{N+h} & 0 & 0 \\ \frac{-\tan\varphi}{N+h} & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta V^e \\ \delta V^n \\ \delta V^u \end{bmatrix} + R_b^l \begin{bmatrix} \delta\omega^x \\ \delta\omega^y \\ \delta\omega^z \end{bmatrix} \tag{3}$$

It also includes the accelerometers biases as follow [7]

$$\delta\dot{f}^b = \begin{bmatrix}\delta\dot{f}^x\\ \delta\dot{f}^y\\ \delta\dot{f}^z\end{bmatrix} = \begin{bmatrix}-\beta_{fx} & 0 & 0\\ 0 & -\beta_{fy} & 0\\ 0 & 0 & -\beta_{fz}\end{bmatrix}\begin{bmatrix}\delta f^x\\ \delta f^y\\ \delta f^z\end{bmatrix} + \begin{bmatrix}\sqrt{2\beta_{fx}\sigma_{fx}^2}\\ \sqrt{2\beta_{fy}\sigma_{fy}^2}\\ \sqrt{2\beta_{fz}\sigma_{fz}^2}\end{bmatrix}\mathrm{w(t))} \quad (4)$$

where β_{fx}, β_{fy}, β_{fz} are the reciprocals of the correlation times associated with the autocorrelation sequence of δf^x, δf^y, δf^y. σ_{fx}^2 , σ_{fy}^2 , σ_{fz}^2 are the variances associated with the accelerometer errors. w(t) is white Gaussian noise with variance equal to one. The gyroscopes drift as follow

$$\delta\dot{\omega}^b = \begin{bmatrix}\delta\dot{\omega}^x\\ \delta\dot{\omega}^y\\ \delta\dot{\omega}^z\end{bmatrix} = \begin{bmatrix}-\beta_{\omega x} & 0 & 0\\ 0 & -\beta_{\omega y} & 0\\ 0 & 0 & -\beta_{\omega z}\end{bmatrix}\begin{bmatrix}\delta\omega^x\\ \delta\omega^y\\ \delta\omega^z\end{bmatrix} + \begin{bmatrix}\sqrt{2\beta_{\omega x}\sigma_{\omega x}^2}\\ \sqrt{2\beta_{\omega y}\sigma_{\omega y}^2}\\ \sqrt{2\beta_{\omega z}\sigma_{\omega z}^2}\end{bmatrix}\mathrm{w(t)}$$
(5)

Where $\beta_{\omega x}$, $\beta_{\omega y}$, $\beta_{\omega z}$ are the reciprocals of the correlation times associated with the autocorrelation sequence of $\delta\omega^x$, $\delta\omega^y$, $\delta\omega^y$. $\sigma_{\omega x}^2$, $\sigma_{\omega y}^2$, $\sigma_{\omega z}^2$ are the variances associated with the gyroscope errors. w (t) is white Gaussian noise with variance equal to one. Finally, the state equation for the INS errors is

$$\dot{X}^l = \begin{bmatrix}\delta\dot{r}^l\\ \delta\dot{V}^l\\ \dot{\Psi}^l\\ \delta\dot{\omega}^b\\ \delta\dot{f}^b\end{bmatrix} \quad (6)$$

2.2 INS/GPS integration model

The errors estimate from the EKF are fed back in order to correct the INS, then EKF output estimates are reset to zero. This type of error feedback mechanism is called closed loop. These errors are applied on iteration of mechanization, with feedback from EKF periodically updating the IMU errors. There are different INS/GPS integration models have been proposed to achieve the optimum advantage depending on the requirements and the applications; such as loosely coupled, tightly coupled and ultra-tightly coupled. The loosely coupled is used in this paper. In which The GPS and INS work independently and provide separate navigation solutions, the GPS output is fed to the EKF, also the INS solution is supplied to the filter which takes the difference between the two and estimates the INS errors. The INS solution is corrected for these errors to produce the integrated navigation solution in the form of position, velocity, and attitude. It is simple to implement and is robust, it provides two solutions for closed loop which are GPS raw data and the integrated solution. The main disadvantage is its inability to provide GPS aiding when the effective number of satellites falls below the minimum. The system model of discrete form EKF for loosely coupled integration is the state vector includes error components of position, velocity, attitude, accelerometer biases, and gyroscope drifts as

$$\delta X_{15*1}^l = [\delta r_{3*1}^l \ \delta V_{3*1}^l \ \delta \varepsilon_{3*1}^l \ \delta \omega_{3*1}^l \ \delta f_{3*1}^l \ ]^T$$
(7)

where G is the noise distribution vector, which includes the variances associated with the state vector as follow

$$G = \left[\sigma_{r,1*3} \ \sigma_{V,1*3} \ \sigma_{\varepsilon,1*3} \ \sigma_{\omega,1*3} \ \sigma_{f,1*3}\right]^T \quad (8)$$

Where F is the dynamic matrix contains the INS error models for the states, which can be written as

$$F = \begin{bmatrix}0_{3*3} & F_r & 0_{3*3} & 0_{3*3} & 0_{3*3}\\ 0_{3*3} & 0_{3*3} & F_V & 0_{3*3} & R_b^l\\ 0_{3*3} & F_\varepsilon & 0_{3*3} & R_b^l & 0_{3*3}\\ 0_{3*3} & 0_{3*3} & 0_{3*3} & F_\omega & 0_{3*3}\\ 0_{3*3} & 0_{3*3} & 0_{3*3} & 0_{3*3} & F_f\end{bmatrix} \quad (9)$$

Where, δZ_k is the measurement vector which consists of the differences between the position coordinates (latitude, longitude, altitude) and velocity components predicted by the INS and the corresponding values measured by the GPS as follow

$$\delta Z_k = \begin{bmatrix}\varphi_{INS} - \varphi_{GPS}\\ \lambda_{INS} - \lambda_{GPS}\\ h_{INS} - h_{GPS}\\ V_{E,INS} - V_{E,GPS}\\ V_{N,INS} - V_{N,GPS}\\ V_{U,INS} - V_{U,GPS}\end{bmatrix} \quad (10)$$

3 Design configuration of proposed system

All sensors are connected together to set up a prototype INS/GPS integration system. The hardware implementation is shown in figure 1.

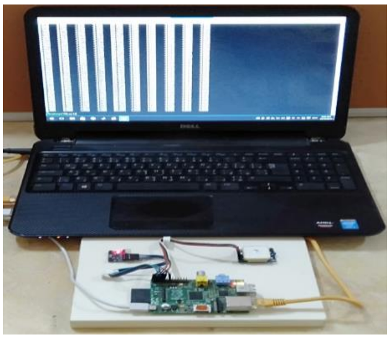

Figure 1, Hardware Implementation

3.1 Software design configuration

The code is written primarily in C++ using object-oriented techniques and necessary libraries to interface between the different sensors are used. All of the code for numerical integration, matrix methods, vector methods, quaternion operations, and Kalman filters has been written in C++. Figure 2, shows the flow chart of the program developed to execute the EKF GPS/INS integration. The designed software adopts the loosely coupling integration strategy [1] where the GPS position and velocity are used to update the INS computed navigation solution. The six remaining states for the sensors errors estimations are neglected and these errors are assumed to be perfectly estimated during the intensive calibration procedure as discussed in the previous chapters. Indeed, better performance is expected to be obtained if a higher grade processor is employed and all the KF states are estimated together. A typical programming procedure is illustrated in Figure 2, where it can be seen in the following flowchart, the program starts from initializing the different sensors, then the initial position states are obtained from the GPS module and pressure sensor. As the vehicle start from stationary, the initial velocity components are equal to zero. Finally, the initial attitudes are computed from initial alignment sub program. At this point, the mechanization loop starts to calculate the navigation states using the initial values and IMU readings. During mechanization loop, the aiding measurements are obtained at certain time loop to be used in Kalman filter update. The correction errors for the navigation states are computed from the Kalman filter sub routine and the subtracted from the estimated states. These corrected states are fed back to be the initial states.

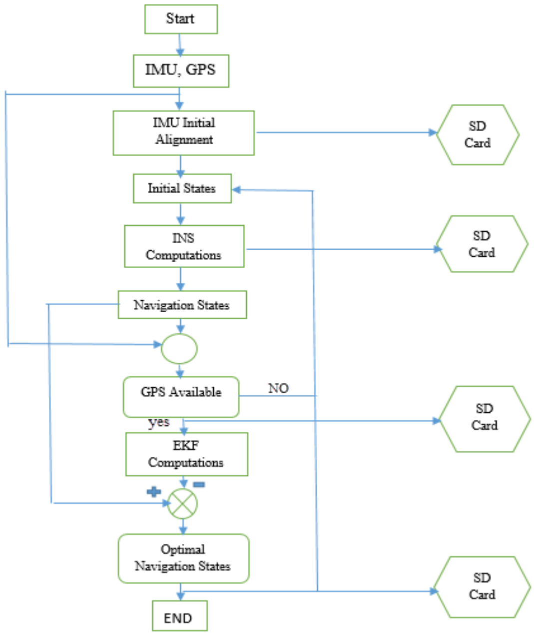

Figure 2, Software Design Configuration

3.2 INS/GPS integration system implementation

In this section, the experiment in the motion mode starts from point (latitude 30.093283 degree, longitude 31.376692 degree, altitude 101.4 m) to point (latitude 30.094885 degree, longitude 31.376750 degree, altitude94.2 m). The experiment is divided into four main parts. The first part is the sensors outputs of MPU 6050 without mechanization. The second part is the navigation solution using the MPU-6050 IMU as a standalone system through the sensors mechanization and without GPS correction. The third part is the KF and GPS were introduced to the system in order to show the KF impact to overcome the errors of the IMU. In the fourth part show what occur in GPS outage intervals. The resulting INS/GPS integration system navigation solutions using kalman filter are shown in figures 3,4. These figures show the difference between the stand alone INS results in blue line and with the GPS aiding using the EKF INS/GPS integration in red line.

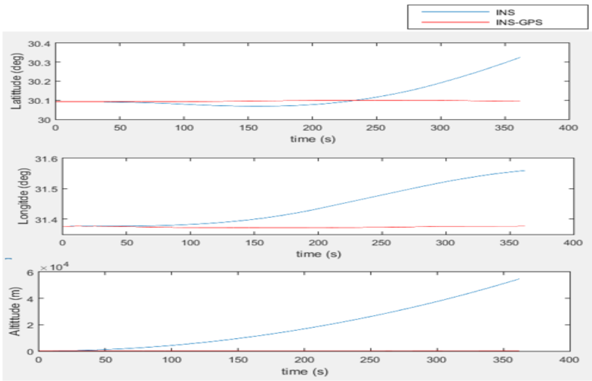

Figure 3, Position of INS/GPS Integration System and INS Standalone

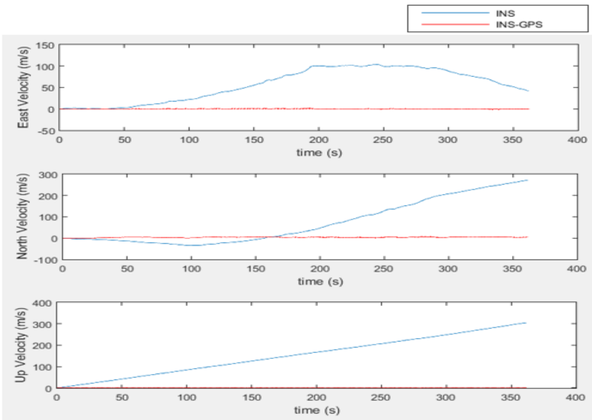

Figure 4, Position of INS/GPS Integration System and INS Standalone

TABLE 1 Comparison between three systems

	INS only	GPS only	Proposed system
Rate	20 ms	1s	20 ms
Start	Lat 30.09328 Lon 31.37669	Lat 30.09328 Lon 31.37669	Lat 30.09328 Lon 31.37669
End	Lat 30.32560 Lon 31.55968	Lat 30.09489 Lon 31.37675	Lat 30.09489 Lon 31.37675
Accuracy	low	high	high
Used in	-	Low dynamics applications	High dynamics applications

In figure 5, the reference trajectory by GPS only is by red color and the standalone INS trajectory is by blue color. From this figure it is clear that performing navigation using standalone MPU-6050 shows that the performance is largely degrade with time, this is of course due to the accumulation errors of the noisy measurements of acceleration and angular rate.

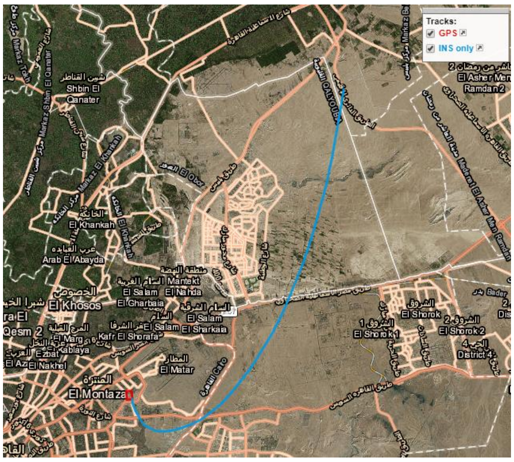

Figure 5, INS Only Trajectory and GPS Reference Trajectory

In figure 6, the reference trajectory by GPS only is by red color and INS/GPS integration system trajectory is by blue color. From this figure it is clear that Integration of INS with GPS improves the excellence of INS performance.

Figure 6, INS/GPS Integration System Trajectory and GPS Reference

GPS only can be used in low dynamics applications but INS/GPS integration system can be used in high dynamics applications. Table 1, show comparison between three systems results.

4 Conclusion

This paper has shown the actual combination of multi-different sensors as (GPS and IMU), each with their own faintness and fortes. As the GPS has a long-term stability and delivers decent results, but it is only accomplished of determining position every second due to its low sampling rate. On the other hand, the low cost IMU has high sampling rate but has low short-term accuracy and cannot be running by itself and delivering any reasonable navigation information. Hence the individual systems by themselves are not enough to give us a good and accurate measure of the navigation states, but these sensors combined have the aptitude of improvement the accuracy of the INS and producing decent results. INS/GPS integration System using Kalman filter is carried out in order to gain the privilege of combination of the advantages of the short-term precision of INS and long-term stability of GPS. Also, an error analysis is carried out to stand up on the possible sources of errors in this integrated system. The analysis of the present study heads to the following conclusions, The combination used leads to a remarkable decrease in the inertial navigation system cost, Integration of INS with GPS improves the excellence of overall navigation system performance, Using of GPS permits calibration of inertial instrument biases, Using of INS improves the tracking and reacquisition performance of GPS receiver and Kalman filter provides real time arithmetical data related to the estimation accuracy of the error states, which is very valuable for measured error analysis. This paper has also shown the effective combination of multi different sensors as (GPS and IMU), each with their own weaknesses and strengths. As the GPS has a long-term stability and provides good results, but it is only capable of determining position every second due to its low sampling rate. On the other hand, the low cost IMU has high sampling rate but has short term accuracy and cannot be running by itself and providing any reasonable navigation information. Hence the individual systems by themselves are not enough to give us a good and accurate measure of the navigation states, but these sensors combined have the ability of improvement the accuracy of the INS and producing good results. Generally, it can be said that the integration of INS with GPS using Kalman filter helps improving strangely the accuracy of navigation data (position and velocity) at low cost sensors. So, the cost of real applications can be reduced and the development of new applications may be made possible.

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