MULTIPLE SENSOR INTEGRATION FOR AUTONOMOUS VEHICLE NAVIGATION

Martin Ernesto OREJAS¹ - Ľuboš VÁCI² - Milan SOPATA³

Abstract: This paper presents a software solution for multiple sensor integration for autonomous vehicle navigation. The system unique features and shortcomings are taken into account to implement the fusion of an inertial navigation system (INS) with measurements from global navigation satellite system (GNSS), altimeter, odometer and magnetometer employing a complementary extended Kalman filter to produce an accurate, reliable and robust navigation solution. The aim of this work is to present specific problems and solutions of sensor integration.

Keywords: INS, GNSS, Kalman filter, navigation system integration, sensor fusion

1. INTRODUCTION
Nowadays there is an increasing demand for low-cost, low-weight precise navigation systems, a clear example being unmanned vehicles (UAVs), and the development of such systems has been boosted by the advent of low-cost MEMS inertial sensors. This has had a profound impact in the development of integrated GNSS/INS systems; while the equations to integrate INS with GNSS are well known, new challenges arise when using low-cost COTS sensors [10]. The inclusion of other sensors as barometer, odometer and magnetometer in the navigation solution becomes of major importance when trying to overcome some of the inherent problems that appear when working with MEMS sensors.

The integration of inertial navigation systems with global navigation satellite systems is a logical step due to the complementary characteristics of each system. An INS is precise for a short span of time, can be run at high frequency and doesn’t depend on external signals however, will drift over time if it is not corrected due to bias accumulation in the process of integrating accelerations and angular rates. On the other hand, a GNSS has a bounded error but run at slower frequencies and is dependent on external signals, therefore can suffer outages. In these situations, a filtering technique called the complementary filter allows an optimal filter to be designed to minimize the effect of the errors on the signal estimate [10].

In the complementary-filter approach, the INS is the primary navigation system that calculates the navigation states at high rate and uses the measurements from aiding sensors coming at lower rates. In our system, a loosely coupled integration was used for the INS/GNSS integration, expanded with additional sensors like barometer, magnetometer and odometer. A complementary extended Kalman filter was implemented to estimate the error of the INS states.

The paper is organized as follows: In chapter 2 the equations necessary to implement INSs are described. In chapter 3 we present the error equations that will be necessary to perform the error state estimation. The models used for the inertial sensors are introduced in chapter 4. Chapter 5 deals with the equations used to develop the complementary EKF and the next chapter give a short description of the fault detection and exclusion algorithm used evaluate the occurrence of a wrong measurement. Chapter 7 contains some brief comments about the integration of additional aiding sources to our system. The following chapter outlines the basic steps for the online initialization and alignment of the IMU platform. The results of our simulations are showed in chapter 9. Finally some remarks about the results and the future plans are provided.

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2. INS MECHANIZATION EQUATIONS

The basic concept [10], [10], [10], of an INS is to integrate accelerations to determinate velocity and position in a desired coordinate frame. Considering the possibility of relative angular motion between frames, gyroscopes are required to maintain the sensor-to-navigation frame transformation. Figure 1 illustrates the functional and operational concept of INS mechanization.

Figure 1 INS block diagram

The continuous time INS mechanization equations are expressed by following set of equations [10].

\[ \dot{r}^n = D^{-1} v^n \]

\[ \dot{v}^n = C^n_a a^b - \left( 2 \Omega^a_{ic} + \Omega^a_{cn} \right) v^n + g^n - \Omega^a_{ic} \Omega^{n}_{ic} v^n \]

\[ \dot{C}^b_n = C^b_n \left[ \Omega^b_{ib} - C^b_n \Omega^a_{cn} + C^e_n \Omega^{e}_{ic} \right] \]

Where

\[ D^{-1} = \begin{bmatrix} 0 & 0 & 0 \\ \frac{1}{\left(R_n + h \right) \cos \phi} & 0 & 0 \\ \frac{1}{\left(R_n + h \right)} & 0 & -1 \end{bmatrix} \]

Where

- \( r^n \) = position in navigation frame
- \( v^n \) = velocity in navigation frame
- \( g^n \) = gravity in navigation frame
- \( a^b \) = acceleration in body frame
- \( \Omega^a_{ic} \) = antisymmetric matrix of angular rate between inertial and Earth frame expressed in navigation frame (Earth rotation)
- \( \Omega^a_{cn} \) = antisymmetric matrix of angular rate between Earth and navigation frame expressed in navigation frame (transit rate)
- \( \Omega^a_{ib} \) = antisymmetric matrix of angular rate between inertial and body frame expressed in body frame (sensors measurement)
- \( C^b_n \) = Direction cosine matrix (DCM) from body to navigation frame
- \( C^e_n \) = Direction cosine matrix from Earth-Centred-Earth-Fixed to navigation frame.

The attitude equation was implemented using quaternion algebra to avoid singularities in attitude angles computation. The attitude dynamics expressed by quaternions are
\[ \dot{q} = -\frac{1}{2} \Omega^b_{nb} \cdot q \]

3. STRUCTURE

A classical approach for the development INS error equations is by perturbation analysis, where the navigation parameters are perturbed with respect to the true navigation values. This approach applies the Taylor series expansion on the continuous INS mechanization equations and retains only the constant and linear terms. The derivation of the perturbation model is described in many studies and literature \[1\], \[2\], \[3\], \[4\], \[5\], \[6\], therefore only a brief derivation will be presented.

Velocity errors are simply the error in the velocities computed in the navigation frame
\[ \ddot{v}^n = v^u + \delta v^n \]

Position errors are obtained from the Earth-Centred-Earth-Fixed to navigation frame DCM, where the computed or perturbed DCM is represented as
\[ C^n_e = [I - (\delta \theta \times)] C^n_e \]

In a similar way attitude errors are obtained from the navigation to body frame DCM.
\[ C^n_b = [I - (\phi \times)] C^n_b \]

If we assume the error equations for measured acceleration, computed gravity vector and computed and measured angular rates as
\[ \ddot{a}^u = a^u + \delta a^u \]
\[ \ddot{g}^n = g^n + \delta g^n \]
\[ \ddot{\omega}_{lu}^u = \omega_{lu}^u + \delta \omega_{lu}^u \]
\[ \ddot{\omega}_{le}^u = \omega_{le}^u + \delta \omega_{le}^u \]
\[ \ddot{\omega}_{in}^u = \omega_{in}^u + \delta \omega_{in}^u \]

We get the following set of equations describing the INS perturbation model \[1\]
\[ \delta \dot{\theta} = \delta \omega_{en}^n - \omega_{en}^n \times \delta \theta \]
\[ \delta \dot{v}^n = v^n \times (2 \delta \omega_{le}^u + \delta \omega_{en}^n) - (2 \omega_{le}^u + \omega_{en}^n) \times \delta v^n + a^n \times \phi + C^n_b \delta a^b \]
\[ \phi = \delta \omega_{en}^n + \omega_{le}^u \times \delta \theta - \omega_{in}^n \times \phi \]

4. SENSORS MODELING

Although the importance of having a good model for the sensors is often neglected, the way the sensors are modeled has a great influence in the overall system performance. Which errors will be taken into account will not only depend on the sensor type and quality but also the application and the environment where the sensors and system are to operate. For low-grade sensors, as the ones used in our system, usually three sources of errors are modelled: a constant bias, a varying bias and white noise. There are many possibilities when modelling a varying bias and a common method is to use a Gauss-Markov (GM) process, or as a particular case of this, a random walk. Thus, the sensor output can be expressed as
\[ \tilde{y} = y + \delta y \]
\[ \delta y = b_{\text{const}} + b_{\text{GM}} + w \]
\[ b_{\text{GM}}(t) = -\frac{1}{\tau} b_{\text{GM}}(t) + w_{\text{GM}} \]

where \( w \) is zero mean white noise and \( w_{\text{GM}} \) is white noises which drives GM process. Time constant of GM is defined by \( \tau \). This model can be further simplified if an estimation of the constant bias is done in the initialization routine leaving only the varying bias and the white noise as the error sources of the sensor.
5. COMPLEMENTARY EXTENDED KALMAN FILTER

In an INS implemented in the complementary filter structure, the output of the INS provides the navigation solution and the EKF estimates the INS errors. The INS error vector is fed back to correct the INS internal states \[1] and \[10]. This is illustrated in 5.

\[\text{Figure 2 } \text{Feedback implementation of the complementary extended Kalman filter}\]

The nonlinear extended Kalman filter is by far the most common method used for integrating INS with GPS. In fact, the error equations presented in chapter 2 are already a linear version of the actual INS error equations so it is not necessary to compute any Jacobian to obtain \( H \) and \( F \) matrices, required for the Kalman filter. Instead, \( F \) and \( H \) matrices can be obtained directly from the errors equations such that they satisfy

\[
\begin{align*}
\dot{x}(t) &= F(x(t)) \cdot \dot{x}(t) + \Gamma(x(k))w(t) \\
y(t) &= H(x(t),t) \cdot \dot{x}(t) + v(t)
\end{align*}
\]

where \( y \) represent the residuals created from the INS states and the measurements (coming from the external sensors) and \( w \) and \( v \) are white noises with respective covariances

\[
\begin{align*}
\text{cov}(w(t)) &= Q \\
\text{cov}(v(t)) &= R
\end{align*}
\]

Before introducing the Kalman filter equations we need to discretize the continuous system described above. It is assumed that the transition matrix \( F \) is constant over the sampling period \( T_s \), therefore

\[
\Phi(x(k)) = e^{F(x(k))T_s}
\]

A truncated Taylor series can be used to compute the previous equation. To obtain the covariance \( Q_d(k) \) of the equivalent process noise \( w(k) \) many approximations are available. One of the most simple and common is

\[
Q_d(k) = \Gamma(x(k)) \cdot Q \cdot \Gamma(x(k))^T \cdot T_s
\]

A slightly more complicated formula is implemented in our system but its description is out of the scope of this work.

The Kalman filter has two main steps: the time update and the measurement update. The time update only depends on the system and computes how the estimated errors \( \Delta \hat{x}^- \) and their covariances \( P^-(k) \) propagate through one sampling period.

\[
\Delta \hat{x}^-(k) = \Phi(k-1)\Delta \hat{x}(k-1)
\]

\[
P^-(k) = \Phi(k-1)P(k-1)\Phi(k-1)^T + Q_d(k-1)
\]

The second step is where the measured data (the computed residuals in the complementary filter) is used to improve the estimation of the errors and to compute the new covariance \( P(k) \). First the Kalman filter gain \( K(k) \) is computed as

\[
K(k) = P^-(k)H(k)^T\left[R(k) + H(k)P^-(k)H(k)^T\right]^{-1}
\]
$K$ is then used to compute $P$. There are different techniques to compute the update of $P$ and although, theoretically, they are all equivalent they have different numerical properties. The equation implemented in our system was chosen because of its numerical stability.

$$P(k) = [I - K(k)H(k)]P^{-1}(k)[I - K(k)H(k)]^T + K(k)R(k)K(k)^T$$

Finally the error estimation is computed as

$$\Delta \hat{x}(k) = x^+(k) + K(k)[\hat{y}(k) - \hat{y}(k)]$$

This estimated error will be used to correct the INS states.

6. RESIDUAL TEST

The inclusion of a wrong measurement in the EKF can cause a severe degradation of the navigation solution, therefore, when developing a system to be implemented in a real application it is essential to have some kind of Fault Detection and Exclusion (FDE) algorithm to avoid incorporating erroneous measurements to the filter. This was done using the residuals between the aiding sensors measurements and their predicted values obtained by the INS. From the residuals and their statistical properties a scalar test statistic chi-square distributed with $n$ degrees of freedom is created, where $n$ is the number of measurements used for creating the test statistic. This statistic is later compared with a predefined threshold to evaluate if a failure has occurred. Using the chi-square distribution allows us to test together a group of measurements that are correlated to each other improving the chances to successfully detect a failure.

7. ADDITIONAL SENSORS

As mentioned earlier, when working with low-grade inertial sensors the addition of redundant sensors not only has the potential to greatly reduce the characteristic drift of the unaided INS but also to improve the navigation solution even when GPS is available. For this project three additional sensors were added to our integrated system: a barometer, an odometer and a magnetometer. The barometer is getting a standard addition in this kind of systems and helps to stabilize the vertical channel. The magnetometer is used to assist with the attitude estimation, especially in the absence of GPS signal (nevertheless tests showed that even if GPS is available, the improvement in heading estimation due the addition of the magnetometer is substantial). The whole 3D magnetic vector is utilized for the integration and extra states were added to the Kalman filter to estimate and compensate the iron distortions. The significant benefit of using the magnetometer is apparent when testing the system under extreme conditions as it is shown in chapter 9. For the odometer a one wheel model was used for the integration and currently the two wheels model is being developed. Another extra state was included in the Kalman filter to estimate the scaling.

8. INITIALIZATION - ALIGNMENT

A large contribution to INS performance degradation is caused by wrong initialization. Moreover, large initial system uncertainties could lead to Kalman filter divergence and destabilize the closed loop system. The alignment often consists of two modes: coarse levelling mode, used to estimate tilt (roll and pitch), and a heading alignment mode, used to estimate heading. The coarse alignment is enabled and runs when the vehicle is stationary. MEMS precision makes gyro compassing unfeasible, therefore heading can’t be estimated from the IMU alone while stationary, in motion alignment is an option. Additional sensor aids have to be incorporated in order to obtain heading. When the platform starts moving, the GPS velocity can be used to perform in-motion alignment. Finally, a so called extended coarse alignment mode is enabled that use a complementary filter to refine the initial attitude estimation.

9. SIMULATIONS - TESTS

Several simulations were done in order to analyze the effect of each component of the system on the overall performance. A trajectory generator was used to create the true trajectory used for comparison and to simulate the data from the different sensors. The errors for position, velocity and attitude under normal conditions are shown in 9.
Figure 3  Error of Navigation Solution for position, velocity and attitude. The red lines represent the standard deviation of the error computed by the Kalman filter.

Sensors characteristics are listed in table below.

Table 1  Sensor characteristics

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Noise characteristics</th>
<th>White noise standard deviances</th>
<th>GM process time constant 1/999.95 [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accel.</td>
<td>Bias 7.10^{-2} [ms^{-2}]</td>
<td>1.10^{-2} [ms^{-2}]</td>
<td>9.0001810^{-4} [ms^{-2}]</td>
</tr>
<tr>
<td>Gyros.</td>
<td>Bias 2.10^{-4} [rads^{-1}]</td>
<td>5.10^{-5} [rads^{-1}]</td>
<td>2.2510^{-10} [rads^{-1}]</td>
</tr>
<tr>
<td>GNSS pos.</td>
<td>none</td>
<td>5 [m]</td>
<td>none</td>
</tr>
<tr>
<td>GNSS vel.</td>
<td>none</td>
<td>0.17 [ms^{-1}]</td>
<td>none</td>
</tr>
<tr>
<td>Altimeter</td>
<td>none</td>
<td>8 [m]</td>
<td>none</td>
</tr>
<tr>
<td>Magnetometer</td>
<td>3.10^{-2} [Gauss]</td>
<td>6.5.10^{-3} [Gauss]</td>
<td>none</td>
</tr>
</tbody>
</table>

Simulations showed that the steady-state bounds for position and velocity errors were primarily defined by the GPS errors, i.e. if GPS signal was available the addition of low-cost inertial sensors did not have a significant influence in the position and velocity errors. On the other hand, attitude errors are highly dependent on the inertial sensor characteristics. Also, in case of GPS outage, the inertial sensors quality will define the rate of drift of the navigation solution. This is illustrated in 9 and 9, where a GPS outage if 70 seconds was simulated. The fact that our residual test is able to detect this outage/failure explains the increase in the computed standard deviation and also point out the importance of having such a test, to avoid the inclusion of wrong measurements that could potentially destabilize the system.
It's interesting to notice the effect of the barometer in the vertical position and velocity estimation and how, even in the absence of GPS, position and velocity errors are bounded for this channel due to the redundancy provided by this sensor.

The advantage of having a FDE algorithm capable of testing different groups of measurements together becomes apparent in 9, where a failure in GPS velocity was simulated (odometer was switched off) while GPS position was still available. Clearly the Kalman filter still uses the GPS position data to compute the corrections and avoid a drift in the navigation solution and therefore only a slight increase in position and velocity errors is observed.

Another clear example of the advantage of having redundant measurements and being able to test them separately is shown in 9 where a failure was simulated for the GPS signal while the odometer was enabled. As expected, the position error starts growing but the availability of the velocity measurement coming from the odometer greatly reduce the rate of this growth.
Finally, one of the experiments that were performed under extreme conditions is shown to depict the influence of the magnetometer in the attitude estimation, particularly the heading estimation. The experiment was carried out over an extremely irregular terrain with a heavily oscillating lever arm. The experiment was carried out over an extremely irregular terrain with a heavily oscillating lever arm. 9 describes the heading error (the error was obtained comparing with the heading computed from GPS velocity data) of the integrated system when the magnetometer is enabled and disabled. The three small plots on the right show the extremely noisy measurements collected with the gyroscopes, accelerometers and magnetometer. It is clear that under these conditions the system is unable to track the heading unless the magnetometer is enabled.

Figure 8  Heading error when magnetometer is switched on/off. On the right: Gyroscope, accelerometer and magnetometer data.

10. CONCLUSION
In this paper we discussed the basic principles of integrating inertial navigation systems with global navigation satellite systems and the issues that arise when implementing this in a real system with low-cost COTS sensors. Many design and implementation issues, not covered in the literature, emerge when applying the somehow standard equations use for INS/GNSS integration. Both, simulations and tests, confirmed the importance of adding additional sensors and a FDE algorithm to deal with real application issues like outage of GPS signal or failure in the GPS receiver and also noisy and poor environmental and dynamic conditions. In the near term future, a tightly coupled integration it is planned to be developed, this will allow not only a more accurate solution, due to the increase in the amount of observables and the improvement in the tracking loops of the GNSS receiver, but also will...
permit the GNSS keep aiding the INS even if less than the minimum four satellites, usually needed to obtain a PVT solution, are available.

REFERENCES