One Approach to the Integration of Low-Cost Inertial Sensors and Global Positioning System for Mobile Robots

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Abstract: Mobile robots are reality these days. Advances in the new technologies, including relatively cheap sensors, new communication and internet technologies together with the increases in the computational speed provide significant advances in the mobile robots autonomy. Precise navigation parameters (position, velocity and attitude) play crucial role for mobile robots to respond autonomously. Supplying wrong or not precise navigation parameters to the Guidance and Control System can turn to be catastrophic for mobile robots. In navigation the trend is to use integrated systems. The idea is to integrate more navigation systems and to achieve better navigation accuracy. In this paper a low-cost integrated navigation system was developed where Extended Kalman Filter (EKF) was used for integration of the Global Positioning System (GPS) information and measurements from the single yaw gyro. Extensive practical experiments were carried out to validate the presented approach. The algorithm was tested on a mobile robot platform Itar Pejo and a car. The results show improvements of the integrated navigation system then the GPS and gyro used alone.

Keywords: Inertial Sensors, Global Positioning System, Navigation systems, Extended Kalman Filter, Robotics, Mobile robots.

1. INTRODUCTION

Robots are all around us and there is a feeling that the whole world becomes robotic today. Expectations are that in the years to come the robots will become integral part of our everyday life. They will be personal as the personal computers today and will improve the quality of life of the humans a lot. Most of today’s robots are fixed robots. They pervade in many areas of modern industrial automation and are mainly concerned with tasks performed in a structured environment (Siciliano, et. Al 2009).

Today remotely operated mobile robots operate and explore planets in our Solar system (Matthies, et. Al 2007). Remotely operated mobile robots perform complex tasks in deep sea, mines, minefields and atomic power plants. In parallel as the technology develops the number of mobile robots will significantly increase and mobile robots will dominate in applications and tasks in unstructured and dynamic environments. Dangerous, remote and contaminated environments are just examples.

Navigation has been present for more then thousands years in some form to another. The insects, the birds and almost anything in nature need to navigate from one position to another. By definition, navigation is the process of determination of the navigation parameters (position, velocity and attitude) of the centre of mass, of the moving object.

In navigation the trend is to use integrated systems. The idea of integration of the subsystems into an integrated system is to take advantage of complementary strengths of the subsystems. Kalman filter (KF) represents one of the most popular estimation techniques for integrating signals from navigation systems and is very attractive for the mobile robots due to its simplicity and low computational demand. Its main disadvantage is that it can only estimate linear systems, GPS is insufficient as a stand alone position system. To be able to use it with systems with nonlinear dynamics a natural extension of the KF called Extended Kalman Filter (EKF) is used.

The primary role of the Global Positioning System (GPS) is to provide highly accurate position worldwide (Kaplan, 2006). Position accuracy of GPS positioning is affected by measurement noise (few meters) and signal errors like: multipath of the signal, ionosphere delays, troposphere delays, signal attenuation, ephemeris error, satellite clock error and receiver clock error. Also, the GPS signal is susceptible to jamming. For many mobile robots navigation systems, GPS is insufficient as a stand alone position system. The Differential Global Positioning System (DGPS) overcomes the before mentioned errors and can provide centimetre accuracy. Its high cost being the mayor drawback limits its use to selected customers.
Micro-machined electromechanical system (MEMS) sensors (gyros and accelerometers) are one of the most exciting developments in inertial sensors in the last 25 years (Titterton, 1997). These devices are used in many applications, especially where cost, size and power consumption has been governing parameters. The major drawback of these sensors is the imperfections i.e. the sensed variables are not equal to the real physical quantities (e.g., bias, scale factor, nonlinearity, and random noise). All these errors make the MEMS sensors diverging slowly from the real measurements with time.


In this paper low-cost integrated navigation system was presented. The GPS information is integrated with measurements from the single yaw gyro where Extended Kalman Filter (EKF) was used for the integration. Extensive practical experiments were carried out to validate the presented approach. The algorithm was tested on a mobile robot platform Itar Pejo and a car. The results show improvements of the integrated navigation system then the GPS and gyro used alone.

The paper is organized as follows. Section 2 presents a kinematic model of a mobile robot. Section 3 is reserved for the implementation of the Extended Kalman Filter in the integrated navigation system. The practical experiments and results of the proposed approach are given in section 4. Conclusions and future work are part of section 5.

2. KINEMATIC MODEL OF A MOBILE ROBOT

Assuming two dimensional world, the mobile robot can be uniquely determined by its position and orientation in space. The mobile robot states therefore are \([x \ y \ \psi]^T\), where \(x\) and \(y\) are Cartesian coordinates of the contact point of the wheel with the ground and \(\psi\) is the mobile robot orientation with respect to the \(x\) axis, known as mobile robot heading. If we use gyro for measuring the yaw angular rate \(\omega\), assuming constant known velocity \(V\) of the robot, kinematic model can be used to describe the motion of the mobile robot in space:

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\psi}
\end{bmatrix} = \begin{bmatrix}
\cos \psi & 0 & 0 \\
\sin \psi & 0 & 0 \\
0 & V & 0
\end{bmatrix} + \begin{bmatrix}
0 \\
0 \\
\omega
\end{bmatrix}
\] (1)

This kinematic model of a mobile robot has an advantage of being simple and easy to implement. Although more complex dynamic models of mobile robots exist and can be used as described in (Siciliano, et. Al 2009) and (Julier, 1997), in this paper the kinematic model was used.

3. EXTENDED KALMAN FILTER IMPLEMENTATION

In this section we describe the EKF implementation for integration of the yaw gyro angular rate of the mobile robot and the GPS information. The integrated navigation system algorithm is shown on figure 1. We assume that the mobile robot velocity \(V\) is constant and known. From the GPS receiver we take the latitude \(\varphi\), longitude \(\lambda\) and altitude \(h\) given in the Earth Centered Earth Fixed (ECEF) frame together with the heading \(\varphi_m\).

![Figure 1. Integrated navigation system algorithm](image)

The measured yaw angular rate \(\omega\) is the control input to the kinematic model of the mobile robot given by equation (1). These equations in discrete form are:

\[
\begin{bmatrix}
x \\ y \\ \psi
\end{bmatrix}_{k+1} = \begin{bmatrix}
V \cos \psi \\ V \sin \psi \\ 0
\end{bmatrix} \Delta t + \begin{bmatrix}
x \\ y \\ \psi
\end{bmatrix}_k
\] (2)

The mobile robot coordinates from the kinematic model are in navigation frame. The ECEF spherical coordinates latitude \(\varphi\), longitude \(\lambda\) together with the altitude \(h\) need to be transformed to the navigation frame. We start by first transforming them to the ECEF rectangular coordinates with:

\[
\begin{align*}
x_e &= (N + h) \cos(\varphi) \cos(\lambda) \\
y_e &= (N + h) \cos(\varphi) \sin(\lambda) \\
z_e &= (N(1 - e^2) + h) \sin(\varphi)
\end{align*}
\] (3)

where \(N(\varphi) = \frac{a}{\sqrt{1 - e^2 \sin^2(\varphi)}}\) is the length of the normal to the ellipsoid.
These ECEF rectangular coordinates are then transformed into the navigation frame:

\[ [x_m, y_m, z_m]^T = C_n^e [x_r, y_r, z_r]^T - [x_r(0), y_r(0), z_r(0)]^T \] (4)

where \( x_r(0), y_r(0), z_r(0) \) are the ECEF coordinates of the origin of the navigation frame, \( C_n^e \) is the transformation matrix from ECEF frame to navigation frame (Farell et al. 1999).

EKF implementation is carried out on the following way. The process model is defined with equation (2). The observation model is

\[ z(k) = h(x(k), v(k), k) \] (5)

The observation matrix \( h(k) \) is 3x3 unit matrix. Using the control input \( u(k) \) from the gyro, and the initial values for the state \( x(k) \) and the error covariance matrix \( P(k) \), the phase of prediction of the EKF starts:

\[ \hat{x}(k + 1 | k) = f(\hat{x}(k | k), u(k), 0, k) \] (6)

\[ P(k + 1 | k) = \nabla f_x P(k | k) \nabla f_x^T + \nabla f_u Q(k) \nabla f_u^T \] (7)

Next we obtain the observation vector (measurements) from the GPS receiver \( z(k + 1) = [x_m, y_m, \varphi_m]^T \). Using the prediction of the state vector \( \hat{x}(k + 1 | k) \) and the error covariance matrix \( P(k + 1 | k) \) the update phase starts.

The Kalman gain \( K(k+1) \) is first calculated

\[ K(k+1) = P(k+1 | k) \nabla h_x [\nabla h_y P(k+1 | k) \nabla h_y + \nabla R(k+1) \nabla h_y^T]^{-1} \]

The innovation vector is formed next \( \nu(k + 1) \)

\[ \nu(k + 1) = z(k + 1) - h(\hat{x}(k + 1 | k), 0, k) \] (8)

then we update the estimate

\[ \hat{x}(k + 1 | k + 1) = \hat{x}(k + 1 | k) + K(k + 1) \nu(k + 1) \] (9)

The updated error covariance can be computed with

\[ P(k + 1 | k + 1) = [I - K(k + 1) \nabla h_y] P(k + 1 | k) \] (10)

where \( I \) is identity matrix. The Jacobian matrices \( \nabla f_x(k) \) and \( \nabla h_y(k) \) with respect to the state \( x(k) \) are:

\[
\nabla f_x(k) = \begin{bmatrix}
\frac{\partial f_x}{\partial x} & \frac{\partial f_x}{\partial y} & \frac{\partial f_x}{\partial z}
\end{bmatrix}
\]

\[
\nabla h_y(k) = \begin{bmatrix}
\frac{\partial h_y}{\partial x} & \frac{\partial h_y}{\partial y} & \frac{\partial h_y}{\partial z}
\end{bmatrix}
\]

Equations (5) to (10) are repeated recursively after, as shown on figure 2 (Brown et. al 1997).

![Figure 2. Extended Kalman Filter (EKF) estimation process](image)

4. PRACTICAL EXPERIMENTS AND RESULTS

Before we start with the presentation of the practical experiments and results we will explain the errors in the MEMS inertial sensors which make the MEMS sensors diverging slowly from the real measurements with time. The four main sources: instrumentation, computational, alignment and environment will be examined here. In this paper for the practical experiments we use the Atomic Inertial Measurement Unit (IMU) from the manufacturer Sparkfun electronics. Since only the measurements from the yaw gyro are used, our attention mainly is focused on the errors in MEMS gyros.

4.1 MEMS Gyro Error Characteristics

Instrumentation errors are the primary source of errors and will be examined first. The effect of the errors caused by the bias in the MEMS gyros is visible on long term. Bias of a rate gyro is the average output from the gyroscope when it is not undergoing any rotation (i.e.: the offset of the output from the true value), in \(^\circ / h\) (Woodman, 2007).
A constant bias error of when integrated, causes an angular error which grows linearly with time. When the bias is “known” i.e. estimated it is simply subtracted from the output. In our work we have assumed that no bias is present. This can be done because we operate the sensors for very short periods. In MEMS gyros the thermo mechanical noise is present. As a result the samples obtained from the sensor can be assumed that are perturbed by a white noise sequence with zero-mean and finite variance $\sigma^2$. This noise introduces a zero-mean random walk error into the integrated signal, whose standard deviation grows proportionally to the square root of time (Woodman, 2007):

$$\sigma_\phi(t) = \sigma \cdot \sqrt{\delta t}.$$  \hspace{1cm} (12)

The environment errors mainly due to the changes in the temperature induce changes in the bias. The temperature also influences on the sensitivity of the MEMS gyros. The alignment errors which appear when the sensors are not perfectly mounted in the center of gravity of the vehicle induce additional bias on the integrated signal. In our work we have taken all the measures to avoid the above mentioned errors.

4.2 Results of the Practical experiments

In the process of validation of the integrated navigation system described in section 3 extensive practical experiments were carried out on several locations. First location was the sports hall “Boris Trajkovski” in Skopje, R. Macedonia where on the mobile robot Itar Pejo* (figure 3) laptop computer was mounted for collecting the yaw angular rates and the GPS receiver information. The mobile robot was driven from one waypoint to another. The collected real time data were processed in Matlab, Simulink where off-line simulation was carried out.

Figure 3. Mobile Robot Itar Pejo

The results on figure 4 show the divergent (red line), the GPS (green line) and the estimated (blue line) from the integrated navigation system trajectories.

Figure 4. Practical experiments results on first location (divergent, GPS and estimated trajectories)

Figure 5 shows the divergent (red line), GPS (green line) and estimated (blue line) heading of the mobile robot. These results show improvements of the integrated navigation system then the GPS and gyro used alone.

Figure 5. Practical experiments results on first location (divergent, GPS and estimated heading)

*The mobile robot Itar Pejo is technically supported by Octagon Systems Corporation USA.
Next location for the practical experiments was the Faculty of Electrical Engineering and Information Technologies campus in Skopje, R. Macedonia (figure 6) where the sensors were mounted in a car, as shown on figure 7. The car was driven around the campus and real time data (yaw angular rates and the GPS receiver information) were collected. The idea here is to validate the algorithm in urban environment.

The results on figure 8 show the divergent (red line), the GPS (green line) and the estimated (blue line) from the integrated navigation system trajectories. Figure 9 shows the divergent (red line), GPS (green line) and estimated (blue line) heading. These results show improvements of the integrated navigation system than the GPS and gyro used alone.

Next location for the experiments was the tunnel on the Veles-Skopje highway, see figure 10. The sensors were mounted in a car and the car was driven through the tunnel and real time data (yaw angular rates and the GPS receiver information) were collected.

Figure 11 shows the divergent (red line), GPS (green line) and estimated (blue line) heading. The results on figure 12 show the divergent (red line), the GPS (green line) and the estimated (blue line) from the integrated navigation system trajectories. These results show improvements of the integrated navigation system than the GPS and gyro used alone.

Figure 7. Sensors (Inertial Measurement Unit (IMU) and the GPS receiver) mounted in a car

Figure 8. Practical experiments results on second location (divergent, GPS and estimated trajectories)

Figure 9. Practical experiments results on second location (divergent, GPS and estimated heading)

Figure 10. Topographic map of the tunnel on the Veles-Skopje highway

Figure 11. Practical experiments results on third location (divergent, GPS and estimated heading)
In this experiment as we can see from figure 12 before exiting the tunnel a loss of GPS information occurs. In the algorithm the integrated navigation system i.e the EKF doesn’t know that the information is not valid and updates the position wrong (blue line), see figure 2 for the complete EKF estimation process.

This situation can have severe circumstances and may crash any mobile robot in the tunnel. In this situation when the GPS information is not valid the EKF should not perform the update phase. Using the control input (measured yaw angular rate $\omega$ ) only the prediction phase, equations (6) and (7) are to computed. This solution is shown on figure 12 with the pink line.

5. CONCLUSIONS

In this paper we have presented a low-cost solution for integration of inertial sensors and GPS information. EKF was used for the integration. Extensive practical experiments were carried out on a mobile robot platform Itar Pejo and a car. The results clearly show improvements of the integrated navigation system then the GPS and gyro used alone. These results also show the direction to which the modern navigation systems will develop. The idea is to integrate more sensors and achieve better navigation accuracy. In our future work mobile robot Itar Pejo will be improved. Other sensors will be mounted for example ultra sonic range finders and video cameras. We plan to substitute the kinematic model with the Inertial Navigation (IN) model and implement the complete 6-DOF problem.

REFERENCES


