2011 International Conference on Networking, Sensing and Control
Delft, the Netherlands, 11-13 April 2011

Adaptive Kalman Filtering Based Navigation: An IMU/GPS Integration Approach

A. Fakharian*, Thomas Gustafsson** and M. Mehrfam
*1- Assistant Professor, Department of Electrical and Computer Engineering, Islamic Azad University, Qazvin Branch, Qazvin, Iran, Corresponding Author Email: ahmad.fakharian@qiau.ac.ir
2- Postdoctoral Researcher, Department of Computer Science and Electrical Engineering, System and Interaction Group, Luleä University of Technology, Sweden
** Professor, Department of Computer Science and Electrical Engineering, System and Interaction Group, Luleä University of Technology, Sweden, Email: Thomas.gustafsson@ltu.se

***Abstract*- This paper investigates on the development and implementation of a high integrity navigation system based on the combined use of the Global Positioning System (GPS) and an inertial measurement unit (IMU) for land vehicle applications. The complementary properties of the GPS and the INS have motivated several works dealing with their fusion by using a Kalman Filter. The conventional kalman filter has a fix error covariance matrix in all times of processing. Multi-sensor based navigation system that is implemented in this paper is called data synchronization. Also, multi-rate operations that are compared with conventional Kalman filtering has fix error covariance matrix. Therefore, when GPS outage occurred we have improper treat by kalman filter. In this paper we present an Adaptive method instead of conventional methods. It is shown that proposed method has a better performance rather than conventional method. Experimental results show the effectiveness of the GPS/INS integrated system.**

***Keywords:* global positioning system (GPS), inertial measurement unit (IMU), Kalman filter, navigation,Land vehicle**

I. INTRODUCTION

The commercial development of large autonomous land vehicles in applications such as open-cast mining, agriculture and cargo handling requires the corresponding development of high integrity navigation (localization) systems. Such systems are necessary to provide knowledge of vehicle position and trajectory and subsequently to control the vehicle along a desired path. The sensors commonly are used in these applications can be classified into two broad categories: dead-reckoning sensors and external sensors. Generally, dead-reckoning sensors are very robust, but accumulate errors with time. Some sensors of this type are Inertial Measurement Unit (IMU) and Odometer Sensor. Therefore, they must be periodically reset by using information from external sensors. External sensors provide absolute information by making measurements from known landmarks like Global Positioning System (GPS).

Each of these types has advantage and disadvantage and all of them can give position separately. But because of disadvantage of each sensor, integration of sensors data can be very better and more reliable. In this condition, if we integrate information of each type of sensor, disadvantage of them can be compensated and results of the proposed sensor fusion method will be better than conventional method [9, 11]. GPS/INS integration system has been widely applied for navigation systems, because of their complementary properties.

There are two different approaches for integrating GPS and INS: the loosely coupled and the tightly coupled. In the tightly couple approach, the raw GPS measurements are used to form the measurement equation. The main advantage of tight integration is that even during poor satellite coverage, updating of the INS can still be performed. The disadvantage is mainly that the state vector increase in size because of single kalman filter with both GPS and INS measurement, and this leads to larger processing time.

Advantage of the loose integration method is mainly it's simplicity in implementation and robustness, such that if one of the used sensor be failed, a solution still is given by other sensor and another advantage of this method is lower processing time because of using a smaller state vector. The disadvantage of this method is mainly that it is impossible to provide measurement update form GPS filter, during poor GPS cover.

The integration of inertial measurement unit (IMU) and GPS has done for several applications that need attitude and position of vehicles in different conditions. High performance IMU is very expensive and only is used in military and commercial airlines. Because of the high price of this type of IMU and the needs of some project to IMU, we must use low cost IMU and correct errors with software methods. In this way, several work has been done. Barshan and Durrant-Whyte [1] shown that if we can provide accurate error model of sensors, we can improve efficiency of low cost IMU. Farrell and Barth [2] introduced a very general method to establish an error process model for the INS/GPS navigation system. Abdel-Hamid [4] described several methods for denoising of inertial data and several method of fusion of GPS and INS data. Mc-Neil Meyhew [6] explained some type of sensors that utilize in navigation and method of their fusion. In [5, 7, 8] new approaches for integration of GPS signal for navigation of land vehicles are proposed.

The focus of this paper is on development and implementation of the estimation techniques that increase the integrity of inertial measurement unit (IMU)/GPS navigation loop for land vehicle application and attempt to design a adaptive kalman filter such that when we have GPS outage the filter behavior be better than conventional kalman filter.

The structure of the paper is as follows. Section 2 presents essential background on IMU and GPS sensor technologies and their advantage and disadvantage that may affect on navigation. In Section 3, the system model is described. In Section 4, the kalman filter and adaptive kalman filter are explained. In section 5 system implementation will be described and in section 6 the experimental results are appeared that followed by conclusions in Section7.

II. IMU/GPS SENSORS

The accuracy of the navigation loop is depend on the accuracy of the IMU and GPS sensors that are implemented directly. The greater accuracy of these sensors leads to greater accuracy of overall navigation loop. Brief description of IMU and GPS sensors is as follows.

A. IMU

IMU is Dead-Reckoning sensor of this integration. The primary advantage of IMU on outdoor land vehicles navigation is that the acceleration, angular velocity and attitude data in 3 reference axes are provided directly at high update rates. Thus the velocity and position of the vehicle can also be evaluated. There are disadvantages to use an IMU. The errors are caused by bias in the sensor readings and vibration of the engine of navigation vehicle and the road are accumulated with time and inaccurate readings are caused by the misalignment of the unit's axes with respect to the local navigation frame. But, inexistence of signal transmission, no possibility of jamming or signal loss and high frequency of sampling are the advantages of INS system.

The IMU that used in this paper is a MEMS IMU that comprises of three accelerometers, three gyros and three magnetometers and one temperature sensor for compensation the effect of temperature. These sets of sensors provide the acceleration, rotation rate and orientation of the vehicle respectively, in the body frame, at a frequency of 120 Hz.

B. GPS

The GPS receiver is an external or absolute sensor. Thus the errors in the data are bounded. However, the GPS unit is a low frequency sensor that it's sample rate is 1Hz, thus it provides the state information at low update rates. GPS system has some advantage and disadvantage. Good characteristics of GPS are global coverage, fast acquisition, good accuracy and low price and bad characteristics are loose of signal in some place such as tunnels and between high building and low rate of sampling and multipath problem that signal of satellite is reflected by other surface and is received by receiver that make error in system. The GPS receiver that is implemented in this paper is a GPS mouse that it's sample frequency is 1 Hz.

III. THE SYSTEM MODEL

There are four reference frames relative to a robot navigation, which are the inertial frame, earth frame, navigation frame, and body frame. The inertial frame (i-frame) is a reference frame in which Newton's laws of motion apply. All the inertial sensors make measurements relative to an inertial frame .The inertial coordinate system can take any point as its origin, and three mutually perpendicular directions as its axis. The earth frame (e-frame) has its origin fixed to the center of the earth. There are two different coordinate systems, rectangular and geodetic coordinate systems, to describe the location of a point in the e-frame. The navigation frame (n-frame) is attached to a fixed point on the surface of the earth at some convenient point for local measurements. The body frame (b-frame) is rigidly attached to the vehicle of interest, usually at a fixed point such as the gravity center of the vehicle, which point is also the origin of the body coordinate system. These definitions of all the frames are given in [1].

In this paper, we use a fixed navigation frame (n-frame) for the vehicle dynamics analysis and we should be aware that any movement is related to the body frame (b-frame) shall be projected to n-frame.

A. PROCESS MODEL

In the IMU/GPS supported vehicle navigation, we define a state vector x as follows

$$x = [p\ v\ \ o\ ] \tag{1}$$

Where $p = [x\ y\ z]^t$, $v = \left[v_x\ v_y\ v_z\right]^t$ $o = [\phi\ \theta\ \psi\ ]^t$ represents position, velocity and orientation. The measurements from an inertial sensor are based on the inertial frame (e-frame), and they must be transformed to the n-frame by the knowledge of attitude of the vehicle. We know all movement in the i-frame follows Newton's law, so the dynamic models for the vehicle navigation can be described by

$$\begin{pmatrix} \dot{p} \\ \dot{v} \\ \dot{o} \end{pmatrix} = \begin{pmatrix} v \\ C_b^n a^b - (2\Omega_{ie}^n + \Omega_{en}^n) v_e^n \\ \omega_b \end{pmatrix} \tag{2}$$

In the land vehicle navigation, the vehicle's movement is in a limited geographic area. Therefore, the fixed n-frame is sufficient. Otherwise the geodetic coordinate system needs to be used. For the fixed n-frame, the ω_{en}^n is a zeros vector. The ω_{en}^n in (2) is the rotation rate of the e-frame with respect to the i-frame projected to the n-frame. This is defined as

$$\omega_{ie}^n = C_e^n \omega_{ie}^e\ = \omega_e (cos\,\lambda \quad 0 \quad -sin\,\lambda)^T \tag{3}$$

Where $\omega_e = 7.292115 \times 10^5\ rad/s$ [1] is the rotation rate of the e-frame to the i-frame. λ is the latitude of the origin of the n-frame in the geodetic coordinate system. The ω_{ib}^b in (3) is the rotation rate measurement of gyros in IMU. In (2), the C_b^n is the direction cosine matrix (DCM) from the b-frame to n-frame. Assuming the vehicle has an attitude which can be obtained by three successive rotations of angles φ, θ, and ψ around the x, y, and z axis, respectively. The transformation matrix C_b^n is expressed by

$$C_b^n \ = \begin{pmatrix} c\theta c\Psi & s\phi s\theta c\Psi - c\phi s\Psi & s\phi s\Psi + c\phi s\theta c\phi \\ c\theta s\Psi & c\phi c\Psi + s\phi s\theta s\Psi & c\phi s\theta s\Psi - s\phi s\Psi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{pmatrix} \tag{4}$$

Where s represents sin , and c represents cos and g_n is the gravity vector in the n-frame, which is expressed by

$$g^n = (0 \quad 0 \quad g)^T \tag{5}$$

Where g is the local gravity which is prependicular to n-frame. Really, in (2) a^b is accelration of body with some noise that we model the noise in measurement covariance matrix.

B. MEASUREMENT MODEL

The obtained position from GPS is considered as the measurement set in a Kalman filter and we utilize it for update of the filter estimation. This can be expressed in the following formulation

$$Z_k = P_k + v_{gps} \tag{6}$$

v_{gps} is the GPS measurement noise, which is white with normal probability distribution $p(v)\sim N(0,R)$. The measurement noise matrix $R = diag(\sigma_x^2, \sigma_y^2, \sigma_z^2)$ can be calculated from data that obtain from GPS without in a fix point in working environment.

IV. KALMAN FILTER

A. CONVENTIONAL KALMAN FILTER

The kalman filter [10] is a set of mathematical equations that is based on dynamic model of system. These equations are used to make an estimate of the current state of a system and correct the estimation using any available sensor measurements. Using this filter that really is a estimator-corrector mechanism, leads to the optimal estimation of linearized system and measurement system model. A brief description of Kalman filter is presented in sequel.

The kalman filter is addressed in the general estimation problem of state $x \in R^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{7}$$

With a measurement $z \in R^m$ that is described by

$$z_k = Hx_k + v_k \tag{8}$$

The random variable w_k and v_k represent the process and measurment noises. They are assumed to be independent of each other, white and with normal probability distributions $p(w)\sim N(0,Q)$ and $p(v)\sim N(0,R)$. In practice, the process noise covariance Q and the measurment noise covariance R matrices might change in each time step however in this type, it is assumed that they are constant.

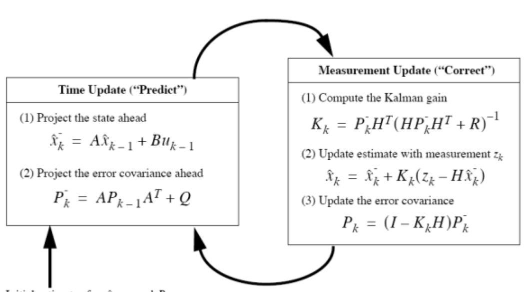

Fig. 1 A complete picture of the operation of kalman filter

B. ADAPTIVE KALMAN FILTER

The estimation accuracy of a conventional Kalman filter depends on a priori knowledge of the system model and the noise statistics. If this knowledge is not successfully accurate, the estimation accuracy will be degraded.

Adapting the filter covariance matrices R and/or Q is one of the remedies to solve the above issue. There are two different implementations of the adaptive Kalman filter [12]. First method is the multiple model adaptive estimation (MMAE) while the other one is an innovation-based adaptive estimator (IAE). In the MMAE approach, a bank of Kalman filters runs in parallel using different models for the statistical filter information matrices R and/or Q. The IAE approach adapts the R_k and/or Q_k matrices based on witheness of filter innovation sequence R_k and Q_k matrices that are adapted as follows

$$R_k = C_k H P_k(-) H^T \tag{9}$$

$$Q_k = K_K C_K K_K^T \tag{10}$$

In above equation R_k and C_k are estimated value of R and Q matrices and C_k is the kth calculated covariance matrix of the innovation sequence which is calculated as follows

$$C_k = \frac{k-1}{k} C_{k-1} + \frac{1}{k} v_k v_k^T \tag{11}$$

the v_k is the kth member of error vector.

V. SYSTEM IMPLEMENTATION

As soon as the process model and measurement model have been established, the adaptive Kalman filter procedure can be implemented directly. The system diagram is shown in Fig. 2.

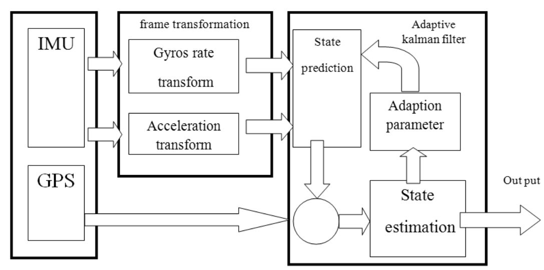

Fig. 2 System implementation diagram

In this system, there is a block that after state estimation by filter, switches the R and Q matrix.

A. FILTER IMPLEMENTATION

For implementation of the adaptive kalman filter, we pay attention to DOP parameter and error propagation of accelerometers and gyroscope of IMU. DOP parameter tells us the effect of weather and environment on the accuracy of GPS. Great value of DOP parameter means low accuracy in position. With this parameter we can recognize the accuracy of GPS. In the other hand, with attention to error propagation in IMU data, we can adapt parameters of R and/or Q matrices data. The (12) and (13) show the accelerometer error propagation in velocity and position as

$$\Delta V_n = n.\sigma.t \tag{12}$$

$$\Delta X_n = n^2.\sigma.t^2 \tag{13}$$

In (12) n is the time step, σ is the error, t is time interval, ΔV_n is the propagation effect of σ in velocity after passing n time interval and ΔX_n is propagation effect of σ in position after same time. In the shown block diagram, we adapt the thresholds in this way that if HDOP[1] effects on the position, was greater than effect of error of IMU sensors, the array in R and Q matrix that is dependent to GPS, switch to greater value and array dependent to IMU takes lower value in some condition with vary great HDOP parameter. It means that we have GPS outage of the GPS dependent array, we take great value for GPS and with calculation of error propagation of IMU we can assign the IMU dependent array to lower value from time to time.

B. SYNCHRONIZATION WITH INS

Usually, measurement frequency in IMU is higher than that in GPS and their measurement times will not be coincident (Fig. 3). In real time, linear extrapolation is used to obtain the IMU's predicted position at the time that GPS gets its position by the following equations

$$P_{IMU}(t_{GPS}) = P_{IMU}(t_{k-1}) + \frac{P_{IMU}(t_{k-1}) - P_{IMU}(t_{k-2})}{t_{k-1} - t_{k-2}}(t_{GPS} - t_{k-1}) \quad (14)$$

Where P_{IMU} means the predicted position by IMU. We know the IMU always predicts the vehicle state as soon as it gets measurement, and the navigation system starts to estimate its position when the GPS receives measurement data. The previous state prediction that only is based on the IMU can be updated based on the estimation.

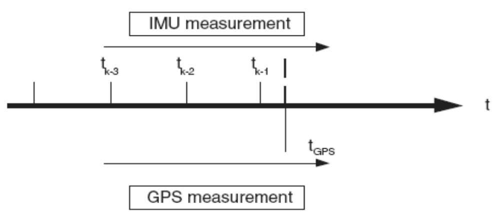

Fig. 3 IMU and GPS measurment time step for linear extrapolation

VI. EXPERIMENTAL RESULT

In our field experiment, two sensors (IMU-MTI and GPS) are installed on the vehicle. The IMU is mounted in the car under hand brake lever and the GPS is mounted on the top of the car that shown in Fig (4).

Fig. 4 IMU mounted at the center of vehicle under hand brake lever

[1] horizontal dilution of precision

In the experiment we set the sampling frequency of IMU to 100Hz and 1Hz for GPS. The experiment was implemented in the square of town that it's map from google earth shown in Fig (5).

Fig. 5 experiment field map

This path contains all simple and circular path that we can test all mode of movement on our algorithm. The mounted IMU was reset with software command to accurate aligning with the axes of vehicle. The strapdown IMU is very sensitive to noise and environmental conditions. Therefore, we use mean filter for denoising and then use it for state estimation and filtering. In Fig (6) the raw data from accelerometer and gyroscope are shown.

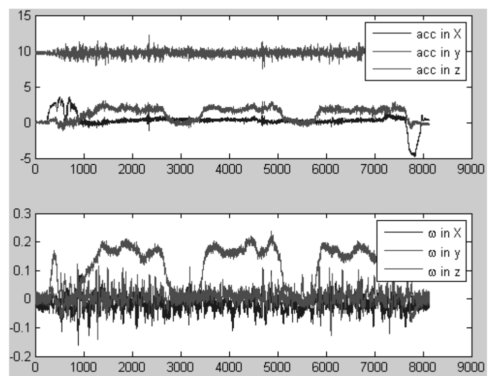

Fig. 6 raw measurement data from IMU.top is acceleration and bottom is angular velocity

The IMU is a dead reckoning sensor, and any noise and bias in the measurement of accelerometer in the IMU will cause second order deviation for its position estimation and any noise and bias in the measurement of gyro in the IMU will change the estimate of the direction of vehicle greatly.
So the measurements from a strapdown IMU can only be reliable for a very short time. Therefore, we must reset IMU data with GPS to hold it in a bounded area near GPS. in Fig (7), results of each sensor separately and result of integration of sensors has been shown. Fig (8) is the same trajectory with 10 second of GPS outage. Fig (9) shows the signal of IMU after filteration by the proposed kalman filter.

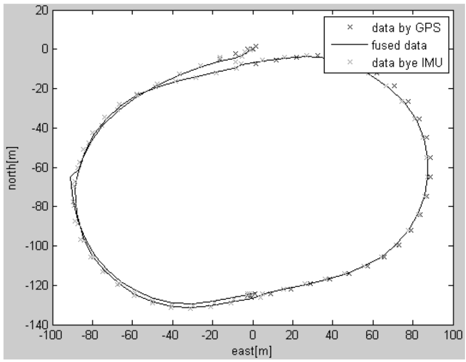

Fig. 7 trajectory given by each sensor and the result of integration

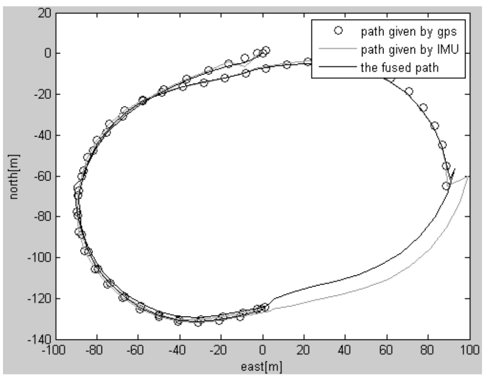

Fig. 8 path given by each sensor and fused path

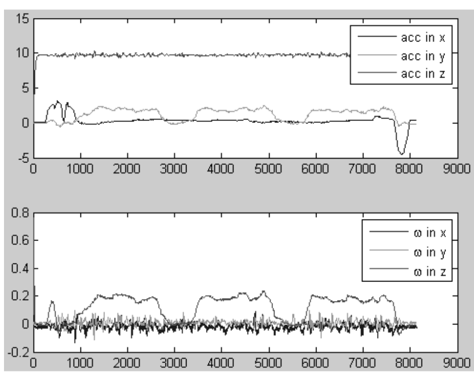

Fig. 9 signals after filtering, top shows the acceleration from accelerometer and bottom shows angular velocity

VII. CONCLUSION

We present a vehicle navigation method by integrating the measurements of IMU and GPS. The measurement of an inertial sensor is based on the i-frame and the measurement of a GPS receiver is based on the e-frame, but the vehicle navigation is based on a fixed local n-frame. So the dynamic models for the system process include the associated transformations from the i-frame and e- frame to the n-frame. In this work we assign a block to supervise on state estimation and with proportion of estimation it updates the error covariance matrix. This method was evaluated by the experimentation on a land vehicle equipped with IMU and GPS on the several points of town.

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