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Improvement of Navigation Accuracy using Tightly Coupled Kalman Filter

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ABSTRACT

In this paper, a mechanism is designed for integration of inertial navigation system information (INS) and global positioning system information (GPS). In this type of system, a series of mathematical and filtering algorithms with Tightly Coupled techniques with several objectives such as application of integrated navigation algorithms, precise calculation of flying object position, speed and attitudes at any moment. Obviously, GPS speed information will contribute to make better estimates of the state in addition to location information. Typically, Kalman filter provides optimal method for states estimation and also creates possibility of combining several measurements to acquiesce a united estimate of system status. Tightly Coupled Kalman filter is a novel and applicable approach to effectively track path with high accuracy especially when four satellites are not available or satellite system stops along the route. Indeed, an important advantage of integration with Tightly Coupled filtration is related to application of software system rather than hardware which somehow reduces hardware complexity and also other advantages of sensors integration is associated with application of all benefits of various sensors as well as covering their individual imperfections in order to increase navigation accuracy. Generally, in integration systems exact GPS observations are used to estimate and INS errors modification by Kalman filter. It is expected that an integrated system with high-precision provides an accurate estimation of all unknowns' parameters and states through kalman filter. Simulations executed for integrated navigation system demonstrate that a flying object could sufficiently compensate errors resulting from modeling of inertial navigation that grows integrally over time and also impressively inhibit flying object deviation respect to condition that only GPS location information are available.

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1. INTRODUCTION

In general, tightly coupled Kalman filter (TCKF) is denoted as one of information integration techniques and Kalman filter is known as an applicable tool for information integration and system states estimation during four decades. Inertial navigation system (INS) is used to accurately measure position, velocity and angular position of flying object relative to basis device. In fact, INS is the most important navigation system particularly in military industries due to lack of communication with outside environment. The main advantage of this system is camouflaging itself from enemies' line of sight because of its lack of communication with outside environment [1-4]. The system is capable to generate all navigation parameters using navigation system processing through output measurements of inertial sensors (accelerometers and gyroscopes). The main disadvantages of INS system is related to enhanced navigation errors due to two step integration calculation during temporal intervals in long path and also existence of faults in inertial sensors. In this system, it had been forced to use expensive sensors to reduce the navigational error which greatly increases system cost.

In [1], an adaptive-fuzzy Kalman filter is proposed for integrated INS/GPS to improve accuracy compared to conventional fusion method. In [2], navigation system is studied with stability surface and in reference [3], north-finding algorithm along with alignment process to investigate the relationship between body devices with the computing device in inertial navigation system.

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In literature [4], integration system of INS/GPS/DP within UKF method is used to enhance navigation accuracy estimation and also a hybrid model of strong tracking Kalman filter algorithm (STKF) and wavelet neural network (WNN) is used to compensate INS error in reference [5]. Entirely, several control method such as differential method, Linear and nonlinear filtering and adaptive fuzzy neural network approach are proposed to improve performance of navigation systems in various applications [6-15]. The obtaining results of papers and schemes show that each proposed approach encompass strengths and weaknesses to increase navigation accuracy and somehow could be applied to improve the accuracy of navigation in ships, aircraft, automobiles, GIS mapping, robotics, etc. The method developed in this paper is intended to cover some latest procedures and also has particular capacities as following: firstly, there is no need to simultaneously access four satellites and secondly in case of GPS interruption path routing will be possible with high precision. In the following of this paper inertial navigation system and global positioning system simulation will be implemented through tightly Coupled Kalman filter to improve system performance and accuracy. Moreover, total structure of integrated INS/GPS and error estimation through Tightly coupled GPS/INS(TCGI) method and problem expression and variables used in this paper are described. Finally, error estimation with TCGI and simulation results and conclusion are being addressed [4].

2. LITERATURE SURVEY

Certainly, development of inertial navigation systems is commenced from the early twentieth century when the Germans researchers applied gyro-Compass in ship navigation systems [16-19]. During World War II, these systems progressed and were used in Missile inertial guidance system in V2 and V1 Cruise for the first time. The history of stochastic data processing method development concerned to 1800 AD when Gauss proposed a non-stochastic least squares method to determine problem parameters through using a series of erroneous measurements. In addition, one hundred years later another estimation theory is proposed when filtering techniques were used in probability density functions during 1910 [20-23]. He presented the maximum chance method which had also been used in many applications. The concept of controllability was discovered in 1954 by Kalman and after the invention of Kalman filter in 1960 many attempts were conducted to apply this filter for non-Gaussian and nonlinear systems [24-29]. The most popular approaches which encompass various applications are Extended Kalman Filter (EKF) and additive Gaussian filters techniques.

3. INERTIAL NAVIGATION SYSTEM

Inertial navigation system (INS) has been established with an inertial measurement unit (IMU) and a processor unit so that each IMU has three accelerometers and three gyroscopes which have been installed along three axes perpendicular to each other and measured acceleration and angular velocity along three axes. In this framework, processing unit is responsible for integral calculation and estimation of linear distance. According to mechanical design, IMU can be divided into two main categories as Gimbaled and Strap down. Particularly, Gimbaled IMU scheme has complicated and delicate mechanical moving parts. This type of IMU is often bulky and expensive and will wear out over time therefore usually Strap down IMU is preferred to be used in flying objects. However, unlike Gimbaled scheme in which the gyroscopes only measure small rotation angles with an amount of several tens of degrees, strap down gyroscopes are able to measure full rotation angles in (360 degrees). Generally, IMU are the main components of gyroscopes and a variety of technologies have been used to build them [30-36]. In general, inertial navigation systems based on terrain complications when GPS data are not available demonstrate their importance. Certainly, interference surpassing in such devices is virtually impossible so that they operate completely independently and determine relative position in earth coordinate system with presence of environmental uncertainty. Indeed, inertial navigation system include a mechanism which device position will be updated based on motion sensors output (accelerometers and gyroscopes). The main drawback of this system is the accumulation of errors over time. However, the advantages of inertial navigation system are described as follows.

- After setting the initial conditions, accessibility to external information are not required.
- This system is not affected by weather conditions.
- It is not identifiable and jamming will not be penetrable into system.

3. 1. Velocity and Position Equations The speed equations in the geographic coordinate can be expressed with following equation.

$$\dot{v}^n = f^n - (2\omega_{ie}^n \dot{+} \omega_{en}^n) \times v^n + g^n \tag{1}$$

In Equation (1), $\bar{v}^n = [v_N v_E v_D]^T$ is velocity vector in the geographic coordinate frame. Moreover, $\bar{f}^n = [f_N f_E f_D]^T$ is accelerometer output in geographic coordinate and f^b is output of IMU accelerometer in ground coordinate which can be obtained through multiplying rotation matrix C_b^n by the accelerometer output. However, rotation matrix will be expressed by the following equation.

$C_b^n = C_3C_2C_1$

$$C_b^n = \begin{bmatrix} cos\Psi - sin\Psi & 0 \\ sin\Psi cos\Psi & 0 \\ 0 \quad 0 & 0 \end{bmatrix} \begin{bmatrix} cos\theta & 0 & sin\theta \\ 0 & 1 & 0 \\ -sin\theta & 0 & cos\theta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\phi - sin\phi & \\ 0 & sin\phi cos\phi & \end{bmatrix} \quad (2)$$

$$C_b^n = \begin{bmatrix} cos\Psi - sin\Psi & 0 \\ sin\Psi cos\Psi & 0 \\ 0 \quad 0 & 0 \end{bmatrix} \begin{bmatrix} cos\theta & 0 & sin\theta \\ 0 & 1 & 0 \\ -sin\theta & 0 & cos\theta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\phi - sin\phi & \\ 0 & sin\phi cos\phi & \end{bmatrix}$$

Rotation rate vector of ground coordinate system respect to inertia coordinate ($\overline{\omega}_{ie}^n$) within geographic coordinate system is given by the following equation.

$$\overline{\omega}_{ie}^n = [\omega_e cos\Phi \quad 0 \quad -\omega_e sin\Phi\,]^T \quad (3)$$

In expression (3), $\overline{\omega}_{ie}^n$ is earth rotation speed and $\overline{\omega}_{ie}^n$ is rotation rate vector of geographic coordinate system relative to ground coordinate frame.

4. THE OVERALL STRUCTURE OF INTEGRATED INS/GPS AND ERROR ESTIMATION WITH TCKF

Kalman filter algorithm is used as a data integration technique. Kalman filter as a convenient tool for integrating information. Kalman filter is known as an applicable tool for information integration and system states error estimation during four decades. Kalman filter is introduced as an optimal estimators for linear dynamical systems when process and measurement noises has Gaussian distribution [35, 36]. In this structure, the difference between pseudo-distance measurements and the rate of pseudo distance variation resulting from GPS have been met with corresponding quantities and are inserted into kalman filter through the inertial navigation system to calculate state estimation errors. Then, output of inertial navigation system will be corrected by these errors. In Tightly Coupled Kalman filter structure pseudo-distance measurements or their relative rate of changes can be used but mostly because of including complementary characteristics, both measurements are used. This structure is entitled as centralized integration method due to utilization of only one Kalman filter. Figure 1 shows the general structure of navigation system includes INS inertial navigation and GPS receiver and TKF filter for INS and GPS navigation error compensation [9].

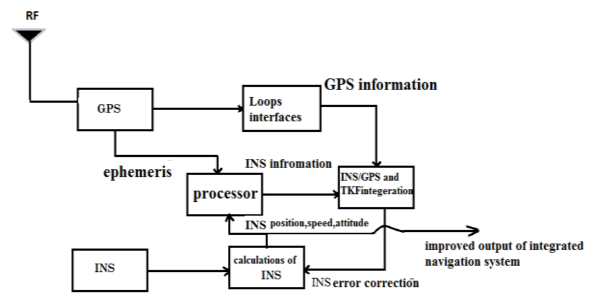

Figure 1. Block diagram of Tightly Coupled structure

Tightly Coupled Kalman filter integration method will facilitate the measurements correlation problems appeared in loosely coupled approach. Moreover, in this data integration method, even if less than four satellites are visible, navigation system continues to track path with high-precision. This method is usually used in vehicles and topographydue to existence of buildings and other obstacles that interrupts communication with GPS [9].

5. MATHEMATICAL ALGORITHM FOR MODELING INERTIAL NAVIGATION SYSTEM (INS) ERROR

Modeling expansion of inertial navigation error (i.eposition, speed and attitude) of a flying object in the Earth's gravitational center is defined as Figure 2.

Inertial navigation systems can be divided into two categories.

A) Inertial navigation system stable platform

(B) Inertial navigation attached rigidlyor “strappeddown” to the body.

In INS stable platform motion parameters (acceleration and angular velocity) is calculated on the frame which is fixed respect to inertial space. In systems attached to the body, motion parameters are expressed in body frame. In this type, inertial navigation is rigid relative to the body and synchronously rotate with its variations. Gyroscopes and accelerometer respectively measure angular velocity and acceleration of a body frame respect to inertial frame and entirely Gyroscopes and accelerometers are established IMU complex. The IMU output data are inserted into onboard computer system during device movement and after post-processing and full filing calculation process speed, attitude and position are determined through navigational algorithm. Meanwhile, inertial navigation system equations are defined as follows [2, 6, 12].

$$\begin{bmatrix} \delta\dot{r} \\ \delta\dot{v} \\ \delta\dot{q} \end{bmatrix} = \begin{bmatrix} \delta v \\ C_b^i(\hat{q})[2A^T R^T \delta q + \delta f\,] + \dfrac{\partial g(r)}{\partial r}\delta r \\ Q(\hat{q})\delta\omega + \Omega(\hat{\omega})\delta q \end{bmatrix} \quad (4)$$

$\lfloor C_b^i(\hat{q}) \rfloor$ is cosine matrix of transformation conductor from flying object body frame to central Earth's gravitational inertia frame, which can be calculated by estimating quaternion at any moment. In error expansion expression, dimension of matrix A is 4*3 which is obtained based on accelerometer and gyroscopes sensors output at any given moment along the path.

Matrix Q(q) dimension in error expansion expression is 4*3 which can be obtained as following based on quaternion estimates at any moment.

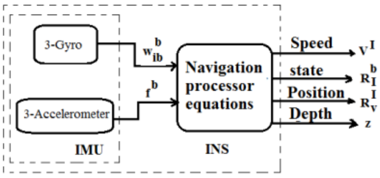

Figure 2. Block diagram of inertial navigation system

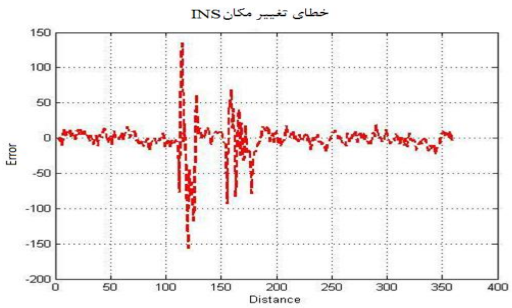

Figure 3. INS error graph along 400 meters path

$$Q(q) = \frac{1}{2}\begin{bmatrix} q_4 & -q_3 & q_3 \\ q_3 & q_4 & -q_1 \\ -q_2 & q_1 & q_4 \\ -q_1 & -q_2 & -q_3 \end{bmatrix} \tag{6}$$

The dimension of matrix R in error expansion expression is 4*4 which can be defined based on quaternion as follows.

$$R = [2Q \quad q] \tag{7}$$

The matrix Ω (ω) (4*4) in error expansion of inertial navigation is obtained according to gyroscope sensors output at any moment.

$$\Omega(\omega) = \frac{1}{2}\begin{bmatrix} 0 & \omega_3 & -\omega_2 & \omega_1 \\ -\omega_3 & 0 & \omega_1 & \omega_2 \\ \omega_2 & -\omega_1 & 0 & \omega_3 \\ -\omega_1 & -\omega_2 & -\omega_3 & 0 \end{bmatrix} \tag{8}$$

To simplify the expression by neglecting scale factor of inertial sensors and short-term error of this sensors except bias instability following expression can be written.

$$\delta\omega = \delta b_g \tag{9}$$

$$\delta f = \delta b_a \tag{10}$$

Using the derived equations, missile dynamic equations in top channel after a linearization can be obtained as follows.

$$\dot{x} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & \frac{\mathrm{sqd}}{\mathrm{I_y}\left(\frac{d}{2U}\right)\mathrm{C_{mq}}} & \frac{\mathrm{sqd}}{\mathrm{I_y}(\mathrm{C_{ma}})} \\ -\frac{\mathrm{S_q}}{\mathrm{mU}(\mathrm{C_w Sin\theta_0})} & 1 & \mathrm{S_q/mU(C_{za})} \end{bmatrix} x + \begin{bmatrix} 0 \\ \mathrm{S_q I_y(C_{m\delta})} \\ \mathrm{S_q/mU(C_{z\delta})} \end{bmatrix} u \quad , \quad y=[1\ \ 0\ \ 0]x \tag{11}$$

where $C_{m\delta}$,$C_{(z\delta)}$,$C_{za)}$,$C_{(ma)}$,C_{mq}, C_W are aerodynamic coefficients, S is reference area of missiles, q is dynamic pressure, m is missile mass, d reference diameter of missiles, U is speed along the x axis and I_y is missiles moment of inertia. Error of inertial sensors (accelerometers and gyroscopes), and regardless of scale factor, INS error curvealong 400 meters path will be described as follows [7].

6. INTEGRATION PROBLEM EXPRESSION AND ITS ADAPTATION NECESSITY WITH TCGI

In general, errors optimization modeling is more accurately defined in integration of INS, GPS while in Kalman filter designing processit is needed to completely well-known dynamic model of process. Furthermore, instable unmolded parameters can essentially "lead to instability of filter".

6. 1. Improve state Estimation with Kalman Filter Algorithm

Indeed, kalman filter is a set of mathematical equations that predicts the current state of the system according to data obtained previously in the system. If we consider discrete Kalman filter and tend to estimate parameter X of system, we can used the following differential equation.

$$\mathrm{X_k = A_{Xk-1} + B_{uk} + w_k - 1} \tag{12}$$

In this model, discrete-time differential equations of INS, GPS integrating systems is used in which state transition matrix and process white noise vector can be defined as follows.

$$\begin{aligned} X_{K+1} &= F_K X_K + W_K \\ Z_K &= H_K X_K + V_K \end{aligned} \tag{13}$$

where Xκ is state vector (n×1), Fκ state transition matrix (n×n), Wκis process white noise vector (q×1), Zκis measurement vector (r×1), Vκis measurement noise vector (r×1), Hκ is r×n matrix. On the other hand, we have:

$$\mathrm{E\{W_K W_K^T\} = Q_K \qquad E\{V_K V_K^T\} = R_K} \tag{14}$$

That $\mathrm{R_K}$ and $\mathrm{Q_K}$are positive definite matrices. Assuming that $\mathrm{R_K}$ and $\mathrm{Q_K}$ matrices are well known Kalman filter algorithm will be defined as follows:

$$\mathrm{\hat{X}_{\overline{K}+1} = F_K X_{\overline{K}}} \tag{15}$$

$$\mathrm{P_{\overline{K}+1} = F_K P_K F_K^T + Q_K} \tag{16}$$

$$\mathrm{K_K = P_{\overline{K}} H_K^T [H_K P_{\overline{K}} H_K^T + R_K]^{-1}} \tag{17}$$

$$\mathrm{\hat{X}_K = \hat{X}_{\overline{K}} + K_K Z_K - H_K \hat{X}_{\overline{K}}]} \tag{18}$$

$$\mathrm{P_K = [1 - K_K H] P_{\overline{K}}} \tag{19}$$

In the above equations $\hat{X}_K$ is estimation of system state vector $X_K$and P_K is covariance matrix of system state estimation error which is defined as follows:

$$P_K = E[(X_K - \hat{X}_K)(X_K - \hat{X}_K)^{-1}] \quad (20)$$

However, to simplify equations and applying Kalman filter, existence noises are considered as normal. Hence, distribution of these noises will be as follows.

$$P(w) \sim N(0, Q)$$
$$P(V) \sim N(0, R) \quad (21)$$

where, Q is the process noise covariance, R is covariance of measurement noise where the standard equation is defined as follows.

$$\dot{X} = Ax + Bu \quad (22)$$

where, x is state vector and u is system input. This expression is a sampled state vector in discrete time while Equation (9) is a sampled state vector in continuous time [8].

Kalman filter is used to predict current system staterespect to previous states and finally, new measurement data will be compared with data anticipated. Therefore, operationsare carried out in two phases named correction and prediction step. The mentioned phases will be listed as following.

$$\mathrm{X}^{\mathrm{k}} - \mathrm{AX}^{\mathrm{KI}} \quad (23)$$

$$\mathrm{P}^{\mathrm{k}} - \mathrm{AP}^{\mathrm{KI}}\lambda\mathrm{IQ} \quad (24)$$

where, K is Kalman coefficient and is defined as follows.

$$\mathrm{K} = \delta\mathrm{X}^2(\delta\mathrm{X}^2 + \delta\mathrm{Z}^2)^{-1} \quad (25)$$

However, this output can be used recursively after performing each measurement in order that in case of error occurrence minimal impacts applied to the system by data sequence. Meanwhile, system correction equation is defined based on following equations.

$$\mathrm{X} = \overline{\mathrm{X}} + \mathrm{K}(\mathrm{Z} - \mathrm{H}\overline{\mathrm{X}}) \quad (26)$$

$$\mathrm{P} = \overline{\mathrm{P}} + \mathrm{KH}\overline{\mathrm{P}} \quad (27)$$

As it is mentioned in above matrix dynamic equations are required.

$$X_t = \mathrm{X}_{t-1} + \mathrm{V}_{t-1}dt \quad (28)$$

$$V_t = V_{t-1} - \left(\frac{k}{m}V_{t-1} + g\right)dt \quad (29)$$

Thus, by concluding from above equations and matrices A can be obtained with respect to time as following:

$$\begin{bmatrix} X_t \\ V_t \end{bmatrix} = A\begin{bmatrix} X_{t-1} \\ V_{t-1} \end{bmatrix} \quad (30)$$

In this approach, integration is conducted by GPS raw measurements which means that difference of pseudo-distance vector measured by inertial navigation system (INS) as shown in Figure 1 will be sent to Kalman filter. Pseudo distance vector will be calculated by INS with the help of available satellite positioning of GPS navigation systems through ephemeris information and flying object position is calculated by INS. In centralized filter integration which is named Tightly Coupled Filter Method only one Kalman filter is used and unlike decentralized approach where the position and speed is calculated on a GPSKalman filter, here GPS raw observations (pseudo-distance or phase) can be entered into Kalman filter along with measured value by INS. The resulting system error estimation will appear as follows using MATLAB software and taking into account the numerical values for position and velocity [8].
X0=0.0,V0=0.0,T=500s,g=0.8,m=1.0,k=10.0,dt=0.01

6. 2. Sources of Error in GPS Carrier Phase Measurements

GPS carrier phase and pseudo-distance measurements errors are influenced by several factors. The sources of errors can be caused by satellite, receiver, receiver clock or signal propagation (reflection from atmosphere layer). The error value generated by any source is simulated in Matlab software. Moreover, mean values of X according to the Equation (20) is calculated, then diversity of positions obtained at any moment from the average is obtained according to the Equation (21) [11].

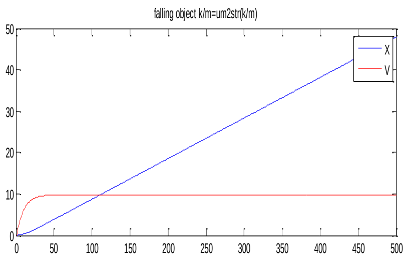

Figure 4. Error estimate of position and velocity by changing Kalmangain in 500 seconds sampling

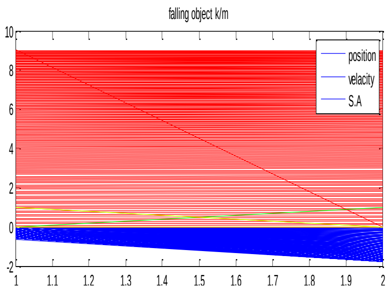

Figure 5. Error estimate of position and velocity by changing Kalman gain in 2 seconds sampling

$$\mathrm{X_{average}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{x_i} \quad (31)$$

$$dx_i = x_i - X_{average} \quad (32)$$

In these equation, $\mathrm{X_{average}}$ has mean value x, $\mathrm{x_i}$ is value for i-th moment and n is numbers of values. Meanwhile, mean and diversity of positions for Y and Z axis is calculated as similar equation. In the following figure an example of dx, dy, dz variation is plotted. To investigate the relationship between x, y, z their correlation will be obtained with following equation.

$$\mathrm{R_{xy}} = \frac{[\mathrm{n}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{x_i\, y_i} - (\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{x_i})(\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{y_i})]}{\sqrt{[\mathrm{n}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{x_i}^2 - (\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{x_i})^2][\mathrm{n}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{y_i}^2 - (\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{y_i}^2]}} \quad (33)$$

According to Equation (30), parameters correlation value are equal to:
Rxz=0.0843, Rxy= 0.5189,R yz=0.1151
These values show that desired parameters are not independent and have a linear relationship with each other.

$$(\Phi + N)\lambda = rr_{su} + c\delta t + \delta\delta_{mp} + \upsilon_{rcvr} \quad (34)$$

$$(\mathrm{\phi_k} - \mathrm{\phi_{k-1}})\lambda = \mathrm{r_{su}, k - r_{su}, k - 1 + c\delta t_{k-1}} + \upsilon'\mathrm{k} \quad (35)$$

where, Φ indicates carrier phase measurements per cycle, N correct carrier phase variable, λ is wavelength of carrier, Rsuis distance between the GPS antenna and satellite, cδt GPS receiver clock error per meter, δcm is ionosphere and ephemeriscommon mode errors and δmp is multi-path signal carrier and υ_{rcvr} is receiver white noise. Generally, measuring carrier phase difference usually used as tripled. In a different study, it was used mostly for debugging errors in navigation tests.

7. THE IMPLEMENTATION OF INS, GPS INTEGRATION ALGORITHM WITH TCKF

Navigation aid systems can also provide speed, attitude or position information but noted that there are various error in their data preparations so that the most important error in the inertia sensor includes a fixed bias error and stochastic noise error. Navigation aid systems in general emerged with this idea that inertial navigation systems include errors such as drift and bias. Hence, various methods have been proposed to address this failure based on GPS application and tightly coupled kalman filter techniques. The following block diagram represents anintegrated INS, GPS system with accelerometer and gyroscope type of errors prediction.

According to disadvantages mentioned about GPS navigation aid systems in this paper software packages such as tightly coupled Kalman filter together with application of the system dynamic model is presented in order to reduce errors in inertial navigation. Since this method does not require additional sensors may not increase operational cost but it encompasses difficulty of estimating step and modeling process error. This method mainly estimates error of inertial navigation systems by using kalman filter which receive difference between output of inertial navigation system and output of base navigation model as an input signal and accumulate it to inertial navigation output. Moreover, GPS receiver sampling rate for high speed and acceleration applications should be in the range of 10 Hz. Therefore, this sampling rate is used in the simulation for GPS receiver. However, in order to compare the results, integrated navigation error will be presented with a sampling rate of 1 Hz. Table 1 shows the filter specifications used in the simulation. By applying these parameters in software of system, we can adopt prediction and correction phase. Moreover, model-based Kalman filter considering linear model, white Gaussian noise is provided and developed for nonlinear systems with time-varying dynamics, other noise types.

Meanwhile, clock bias error and frequency drift of GPS receiver is considered large for error modeling of GPS receiver at the worst case to consider effects of probabilistic error dependent on various conditions. So, receiver clock bias error is set equal to 50 mm (3σ) and a frequency drift equal to 0.02 meters per second and Gaussian noise with a standard deviation of 0.002 meters per second is added on the receiver's frequency to impact on a receiver clock bias as a stochastic process.

TABLE 1. Filter parameters for simulation

Index definition	Symbol	Value
standard deviation VEGPS	σ_{VE}	9.16×10^-4m/s
standard deviation VNGPS	σ_{VN}	9.16×10^-4m/s
standard deviation VDGPS	σ_{VD}	12.6489 m/s
standard deviation in width	σ_{Φ}	3.1360×10^-4 rad
standard deviation in length	σ_{λ}	3.1360×10^-4 rad
standard deviation in height	σ_{h}	60m
Gyro standard deviation in x,y,z	σ_{g}	0.9 deg/h
Accelerometer standard deviation in x,y,z	σ_{a}	1mg
Sampling time	Δt	0.1

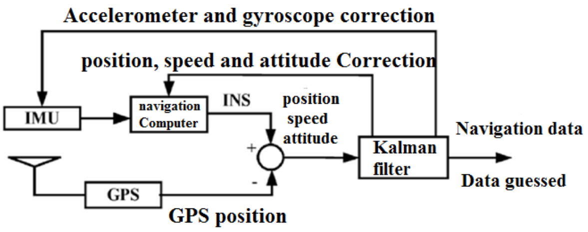

Figure 6. Functional block diagram of position and speed estimation of INS/GPS with Kalman filter

The Tightly Coupled integration resolve measure correlation problem appeared in loosely coupled method. Moreover, even if less than four satellites are visible this data integration method is applicable. However, since this structure treat GPS raw data, its implementation is more complicated than loosely coupled approach. The following figures are considered at different time'ssteps and represent geographical length, width and height during the path.

In Figure 7, integration is sampled with TCGI and TLGI at a distance of 5,000 meters and shows that in TCGI sampling oscillation is less than TLGI mode and in this case navigation system accuracy has been improved.

Figure 8 shows the sampling by GPS and Kalman filter for speed and position toward north and geographical altitude will make less error.

8. SIMULATION RESULTS

The main objective of this paper is to improve navigation system of a flying object through sensor data integration of INS and GPS. Noted that INS is an independent measurement system and can be used in any situation. Moreover, positioning and attitude accuracydecreases with INS during the speed (dependent on IMU Drift rate) but application of GPS observations may limit IMU accuracy reduction overtime.

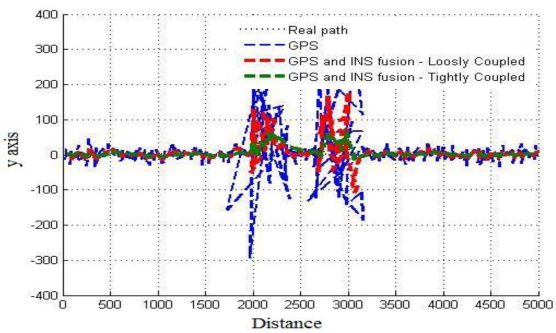

Figure 7. Comparison of position shifting error in the integrated INS/GPS with tightly, loosely coupled

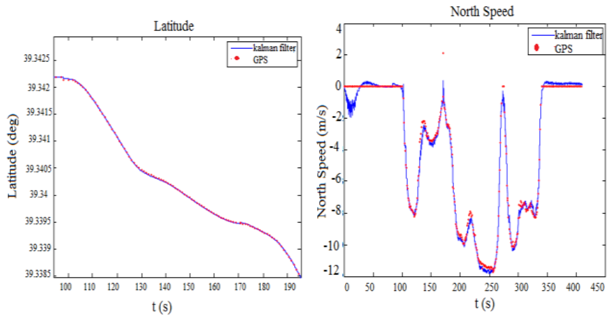

Figure 8. Kalman filter curve and GPS in height and toward north in the 450 and 190 seconds

Also, in case of GPS signal interruption determination of position and attitude by IMU observations will be possible in the limited timeframe. At each step of inertial navigation system, in addition to calculation of inertial navigation, error expansion expression of inertial navigation has been updated. At every step of inertial navigation integration (estimate former system state vector) containing inertial navigation error and inertial sensors error (in addition to former state error covariance matrix) are updated. By taking the distance and speed of satellites, GPS measured initial speed and position estimates at every step and also GPS module Pseudo-distance and pseudo-speed are predicted respect to desired satellites. Accordingly,measurement error resulting from predicted GPS receiver are inserted into Tightly Coupled Kalman filter and corrected error is entered into INS processor using close loop mode and new information are sent into actuators.

9. CONCLUSION

Optimal Information integration algorithm of inertial navigation with GPS has a great effect on navigational error estimates. After the convergence of error estimation, accuracy required for guidance process is provided so that leads to increase the accuracy of spatial maneuvers. As mentioned, a suitable sampling rate of GPS receiverto be used in orbital module is about 10 Hz. Moreover, speed error after proceeding a short time of integration is converged to less than 1.0 meters per second which is totally favorable and stable value respect to utilization of only inertial navigation where its error is time-varying and is about dozens of times.

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Improvement of Navigation Accuracy using Tightly Coupled Kalman Filter

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چکیده

در این مقاله به روشی نوین که بتواند دقت ناوبری یک جسم پرنده را بالاببرد و خطای ناوبری اینرسی وسیله پرنده را در طی مسیرطولانی به حداقل برساند، می پردازیم. در این نوع سیستم‌ها از یک سری الگوریتم‌های ریاضی و فیلترینگ با روش‌های Tightly Coupled با هدفبه-کارگیری الگوریتم‌های ناوبری تلفیقی، دست‌یابی به موقعیت ، سرعت و وضعیت هرچه دقیق‌تر جسم پرنده درهرلحظه است.مزیت مهم تلفیق سنسوری را می‌توان استفاده از تمام مزایای سنسورهای مختلف و پوشش عیوب هرکدام از آن‌ها به منظور افزایش دقت ناوبری دانست. در سیستم‌های تلفیق از مشاهدات دقیق GPS به منظور برآورد و تصحیح خطاهایINS توسط فیلترکالمن استفاده می‌شود. از یک سیستم تلفیق با دقت بالا انتظار می‌رود، همه مجهولات فیلترکالمن شامل(بردارخطای INS، موقعیت، سرعت و پارامترهای دلخواه دیگر) به طور دقیق برآورد شوند. تلفیق سیستم موقعیت یابی جهانی با سیستم ناوبری اینرسی روشی کم هزینه برای تامین یک سیستم ناوبری دقیق و مطمئن درکاربردهای نظامی و غیرنظامی است.

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