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Sensor Fusion for Navigation of an Autonomous Unmanned Aerial Vehicle

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Abstract - **This paper presents the position and velocity determination by using INS and GPS. The measurement results from INS and GPS sensors are fused by using Kalman filter. Dilution of Precision (DOP) technique is used to select a combination of satellites to be used as measurement data. Two implementations of Kalman filter, feedforward and feedback are used. The experiment shows that the selection of the satellites affects the measurements. The methodology and experiments presented in this paper has been developed and tested for the autonomous Unmanned Aerial Vehicle (UAV).**

I. INTRODUCTION

The Inertial Navigation System (INS) is widely used as one component in guidance, navigation, and control systems. It includes accelerometers and gyroscopes, which will be used to calculate position and orientation of the vehicle. The methodology and experiments presented in this paper are applicable to all robotic vehicles but are especially suitable for guidance and navigation of an autonomous Unmanned Aerial Vehicle (UAV).

The nature of the integration process in calculating position and orientation of the vehicle in INS causes propagation error, especially when the INS is implemented in dead-reckoning navigation process. Additional external sensors are often used to bind this error.

Global positioning system (GPS) is commonly combined with the INS to bind its propagation error. These two types of signals are fused together to produce one accurate navigational information. Kalman filter is the common algorithm used to fuse the measurements [1,2, 3, 4].

In [5, 6, 7] authors used an advanced techniques of Kalman filter gain tuning based on fuzzy logic.

There are many research works already conducted to improve position estimation when implementing INS and GPS, whether as a standalone estimation method, or as an integrated system. In [8] authors tried to find the effect of gravity anomalies to the inertial velocity errors. Similarly, in [9] the gravity-induced errors in airborne inertial navigation were analyzed. In [10], a satellite selection criterion was introduced in order to improve accuracy of the estimation when using GPS. In [11] authors used simulated cross-link pseudorange measurement to update the predicted trajectory of the satellite, which, in turn will improve the accuracy of navigation system using standalone GPS.

The distributed Kalman filter simulator (DKFSIM) was introduced in [12]. This filter is used to evaluate the performance of several different filter architectures and sensor model conditions for advanced, multi-sensor navigation systems. In [13], authors examined the integration of INS-GPS for autonomous land vehicle.

Currently, there are 28 global positioning satellites constellation available to be used for navigation. From any particular location, a receiver can view around 10 satellites at any given time. Although, the estimation is usually improved when using more satellites, the channels available to receive the measurement signals are usually restricted. Moreover, not all the visible satellites are good to be used as the sources of measurement, as shown in [10]. Therefore, the receiver has to choose the best combination of satellites in view to get the optimal estimation.

In this paper, INS and GPS measurements data are combined to find the optimal measurement results by using Kalman filter. The INS and pseudorange measurement of the GPS satellites are recorded from aboard of an aircraft flying in a designated path. The best combination of satellites is chosen from a number of visible satellites by using dilution of precision (DOP) technique. The effects of the change of satellites in combination to the estimation are examined.

II. POSITION DETERMINATION BY USING INERTIAL NAVIGATION SYSTEM

Position determination by using the INS can be briefly explained by the following steps:

- Measurement of the accelerations in the directions of the navigation axes. For vertical acceleration, the effect of the earth gravitation has to be included in calculation.
- Determination of distance and velocity by integrating the acceleration. This integration involves time interval, so this interval must be known accurately.
- Measurement of the rotation rates (from gimbals motion in a stabilized platform or from gyroscopes in a strapdown system) as a process to find the direction of the measured distance and velocity. This should include the compensation of the earth's rotation.
- Combining the distance and heading data gives an updated dead reckoned position to display.

III. POSITION DETERMINATION BY USING GPS PSEUDORANGE

To determine user position, GPS uses time-of-arrival of signals broadcast by satellites. The signals contain two types of ranging codes, which are pseudorandom noise (PRN), and navigation data.

In three dimensional spaces, user position can be determined from GPS satellites constellation by measuring the ranges from minimal four satellites positions. Since, the satellites and user receiver clock will generally have a bias error from GPS system time, the ranges determined from this process are called pseudorange (ρ), and contains the geometric satellite-to-user range, an offset caused by the difference between user clock and GPS system time, and an offset caused by the difference between satellites clock and GPS system time.

In three dimensions space, the range can be determined by using the following equations:

$$\rho_1 = \sqrt{(x_1 - x_u)^2 + (y_1 - y_u)^2 + (z_1 - z_u)^2} + ct_u \qquad (1)$$

where ρ_i denote measured pseudorange from satellite i into user position, x_i, y_i, z_i denote the satellites position in three dimensions, c is the speed of light, (2)

$$\rho_2 = \sqrt{(x_2 - x_u)^2 + (y_2 - y_u)^2 + (z_2 - z_u)^2} + ct_u$$

$$\rho_3 = \sqrt{(x_3 - x_u)^2 + (y_3 - y_u)^2 + (z_3 - z_u)^2} + ct_u \qquad (3)$$

$$\rho_4 = \sqrt{(x_4 - x_u)^2 + (y_4 - y_u)^2 + (z_4 - z_u)^2} + ct_u, \qquad (4)$$

where x_i denote user position, and y_i is user receiver clock error.

IV. DILUTION OF PRECISION (DOP)

In determination of position by using GPS, the accuracy of the sensors fusion performance is also influenced by the geometry of satellites distribution, which is known as dilution of precision (DOP). It is defined as geometry factors that relate parameters of the user position and time bias errors to the pseudorange errors.

The more usable satellites that are available result in higher accuracy. In this case, the DOP parameter is calculated from all available satellites.

In this experiment, all available satellites are used as candidates to find user position. To prevent degradation of result, the DOP of the satellites distribution is calculated when new satellite becomes available to use or older satellite becomes invisible. If the resulted DOP lower that predefined value, the satellites combination is recalculated, and chosen base on the smallest DOP.

The DOP parameter can be derived by expanding (1) - (4) in a Taylor series about approximate user position. The error of the pseudorange measurement from the approximate user position in this case can be formulated as:

$$\begin{aligned}\rho_i - \hat{\rho}_i = &-\frac{x_i - \hat{x}_u}{\hat{r}_i}\Delta x_u - \frac{y_i - \hat{y}_u}{\hat{r}_i}\Delta y_u \\ &-\frac{z_i - \hat{z}_u}{\hat{r}_i}\Delta z_u + c\Delta t_u,\end{aligned} \qquad (5)$$

or in matrix form as:

$$\begin{bmatrix}\Delta\rho_1\\ \Delta\rho_2\\ \Delta\rho_3\\ \Delta\rho_4\end{bmatrix} = \begin{bmatrix} a_{x1} & a_{y1} & a_{z1} & 1\\ a_{x2} & a_{y2} & a_{z2} & 1\\ a_{x3} & a_{y3} & a_{z3} & 1\\ a_{x4} & a_{y4} & a_{z4} & 1\end{bmatrix}\begin{bmatrix}\Delta x_u\\ \Delta y_u\\ \Delta z_u\\ c\Delta t_u\end{bmatrix} \qquad (6)$$

Equation (6) can be written in compact form as:

$$\Delta\boldsymbol{\rho} = \mathbf{H}\Delta\mathbf{x}. \qquad (7)$$

From this equation, geometric dilution of precision (GDOP) is defined as:

$$\text{GDOP} = \sqrt{\text{trace}(\mathbf{H}^T\mathbf{H})^{-1}}, \qquad (8)$$

where trace[·] indicates the sum of diagonal elements of [·].

Fig. 1 shows the satellites visibility as a function of time when the INS and GPS pseudorange measurement data are recorded.

V. GPS-AIDED INERTIAL NAVIGATION SYSTEM

In this work, the GPS and INS sensors are used to find the position of the aircraft at particular time. The problem can be summarized as finding the optimal signal on the basis of two different signals available. Kalman filter algorithm is implemented where the measurement outputs from INS and GPS sensors are fused together to find the optimal error state.

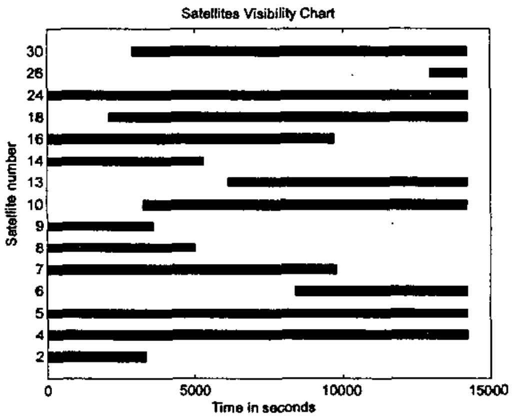

Fig. 1 Satellites Visibility Chart

In general, there are two different implementations of the error state space configuration: feedback and feedforward. These implementations are based on how the estimated errors resulted from the filter are combined with the inertial system. Fig. 2 and Fig. 3 display the appropriate configurations as block diagrams.

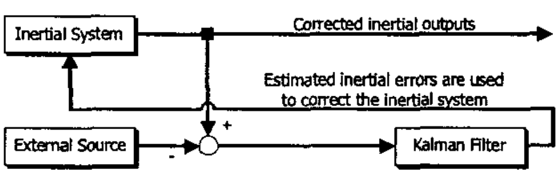

Fig. 2 Error Feedback Kalman Filter

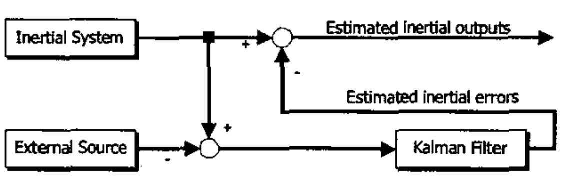

Fig. 3 Error Feedforward Kalman Filter

For 8-state Kalman filter, the dynamic model for the INS measurement can be written as:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \\ \dot{x}_7 \\ \dot{x}_8 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} + \begin{bmatrix} 0 \\ w_2 \\ 0 \\ w_4 \\ 0 \\ w_6 \\ w_7 \\ w_8 \end{bmatrix} \tag{9}$$

or in matrix form as:

$$\dot{\mathbf{x}}(t) = \mathbf{F}(t)\mathbf{x}(t) + \mathbf{w}(t), \tag{10}$$

where $\mathbf{w}(t)$ represents the accelerations and clock noises of the INS sensor. It is assumed that the noise is purely white noise, zero mean, and Gaussian with covariance $\mathbf{Q}$.

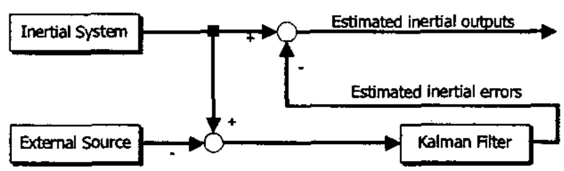

Fig. 4 Error Feedforward Kalman Filter

Transforming (10) into discrete form results:

$$\mathbf{x}_{k+1} = \mathbf{\Phi}_k \mathbf{x}_k + \mathbf{w}_k, \tag{11}$$

where:

$$\mathbf{\Phi}_k = e^{\mathbf{F}T}$$

$$\mathbf{w}_k = \int_{kT}^{(k+1)T} e^{\mathbf{F}[(k+1)T-\tau]}\mathbf{w}(\tau)d\tau$$

The covariance of $\mathbf{w}_k$ in discrete form ($\mathbf{Q}_k$) can be found as:

$$\mathbf{Q}_k = \int_0^T e^{F\tau}\mathbf{Q}\,e^{F^T\tau}\,d\tau. \tag{12}$$

The observation for the Kalman filter is the difference between pseudorange as measured by GPS and the predicted pseudorange, which can be derived from (6). This equation is defined in Earth-Centered, Earth-Fixed (ECEF) coordinate system. Transforming it into local coordinate frame, and writing the matrix as line results:

$$
\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} = \begin{bmatrix} a_{x1} & 0 & a_{y1} & 0 & a_{z1} & 0 & 1 & 0 \\ a_{x2} & 0 & a_{y2} & 0 & a_{z2} & 0 & 1 & 0 \\ a_{x3} & 0 & a_{y3} & 0 & a_{z3} & 0 & 1 & 0 \\ a_{x4} & 0 & a_{y4} & 0 & a_{z4} & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix} \tag{13}
$$

where i denotes the satellites used.

The last term in (13) is the measurement noise. It is also assumed as zero mean Gaussian white noise with covariance $\mathbf{R}$.

Measurement (13) is already in discrete form, so it can be implemented directly into discrete Kalman filter. Writing this equation in matrix form result:

$$
\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \tag{14}
$$

Therefore, we conclude the equations for the GPS aided inertial navigation system as shown by (11) and (14).

VI. EXPERIMENTS AND RESULTS

Simulation experiments have been conducted to show the implementation of the Kalman filter in the GPS-INS sensors fusion. Two implementations of the filter were considered: *error state feedforward and error state feedback Kalman filter.*.

The data for the simulation experiment was recorded from an aircraft flying along a designated path. From the aircraft, the INS measurement, GPS satellites' pseudorange measurement, and the satellites' locations from all visible satellites were recorded.

Fig. 5 displays the path followed by the aircraft during the flight. Although, more that four GPS satellites measurement data were recorded during the flight, only four were used in the experiment. The selection of the satellites used in the experiment was done by using the DOP method as explained before. The simulation experiment has been conducted for 2.5 hours long.

The results of the experiment are displayed as the position and velocity errors. Fig. 6 until Fig. 13 displays the result. The dash line represents the result of the experiment when using error state feedforward Kalman filter and the solid line represents the result when using error state feedback Kalman filter.

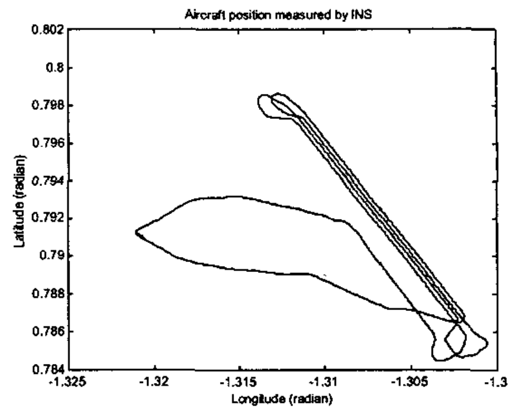

Fig. 5 Path followed by the aircraft during the experiment.

From the figures, it can be seen that the error state feedback Kalman filter implementation results in smaller error than the feedforward one. It can also be seen that there are some spikes of the error. These spikes are resulted when the filter switches into different satellites combination. The switches are needed because one or more satellites used in previous combination are not visible anymore, or because the combination will produce greater DOP value than the other possible combinations.

For filter covariance, shown only for velocity error in East direction, in general the feedback Kalman filter gives smaller uncertainty. It can also be seen that the uncertainty increases before the change of satellite combination occurs. This is reasonable, because when the satellites become not visible, the measurements produced from GPS receiver also become unreliable. From the plot of covariance can be seen that the third combination gives smaller uncertainty than the first two. The third combination also gives good results until the end of simulation. This pattern is valid for position error covariance as well as velocity error covariance.

For Kalman gain, in the first combination, the feedback configuration gives more weight to the INS measurement than the feedforward configuration. The opposite is resulted in the third combination, where the feedback gives more weight to the GPS measurements.

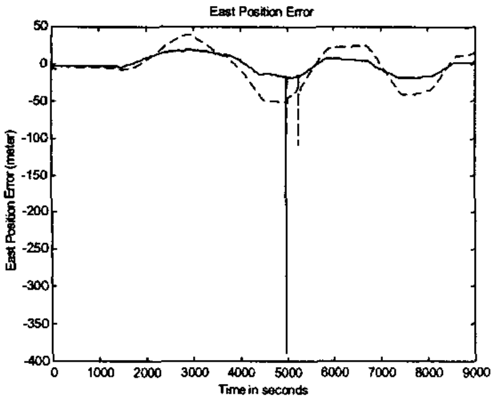

Fig. 6 East position error.

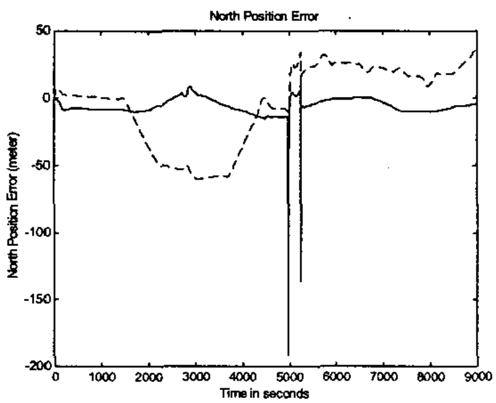

Fig. 7 North position error.

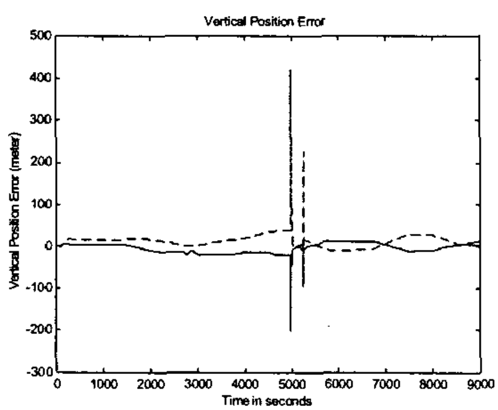

Fig. 8 Vertical position error.

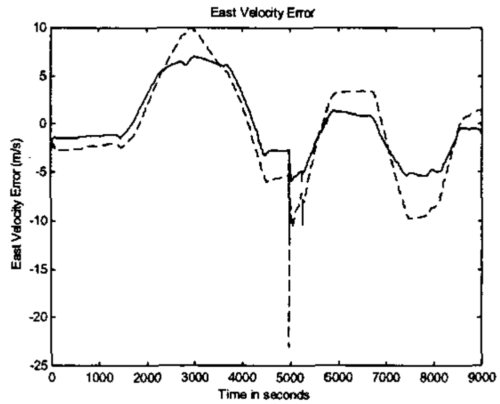

Fig. 9 East velocity error.

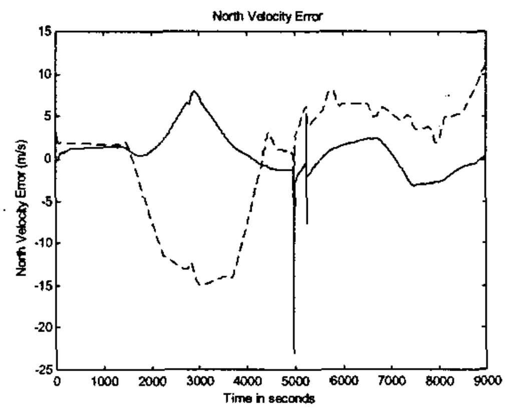

Fig. 10North velocity error.

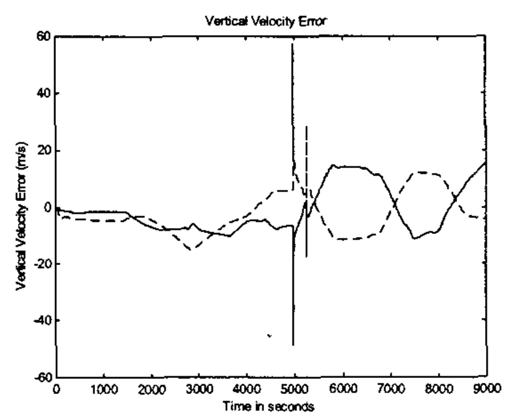

Fig. 11 Vertical velocity error.

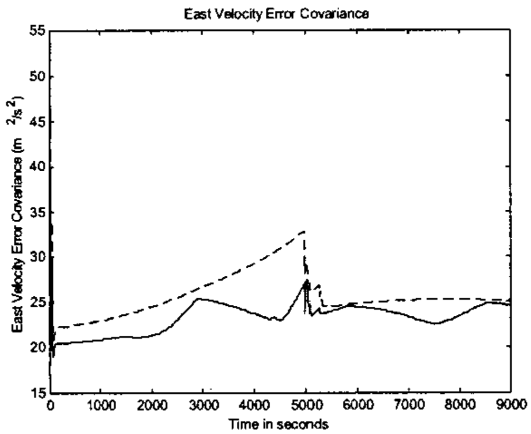

Fig. 12 Velocity error covariance in East direction

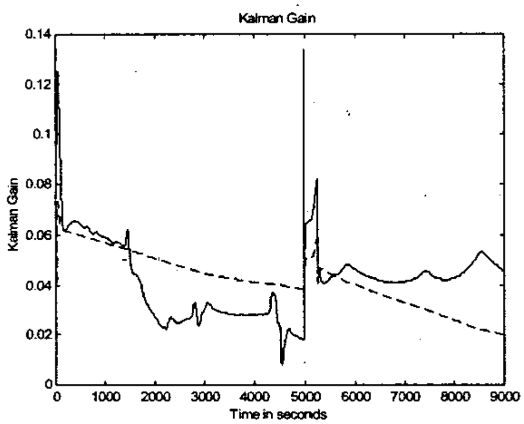

Fig. 13 Kalman gain.

VII. CONCLUSIONS

This paper presents methods and experimental results of guidance and navigation system for autonomous robotic vehicles. The sensor fusion shown in this paper is based on Kalman Filter and analyzes various design approaches. The method was applied to the GPS/INS integration. The algorithms developed allow for real-time operation and control. The experimental results were presented and discussed. This method is an important and useful tool for Unmanned Aerial Vehicles (UAV) guidance and control systems. It greatly improves the positioning accuracy and its autonomous capabilities.

VIII. REFERENCES

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