Direct Kalman Filtering of GPS/INS for Aerospace Applications

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BIOGRAPHY

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ABSTRACT

In integrated navigation systems Kalman filters are widely used to increase the accuracy and reliability of the navigation solution.

Usually, an indirect Kalman filter formulation is applied to estimate the errors of an INS strapdown algorithm (SDA), which are used to correct the SDA. In contrast to that, in the direct Kalman filter formulation total quantities like position, velocity and attitude are among the state variables of the filter, which allows them to be estimated directly.

This contribution investigates the influence of these two different approaches of Kalman filtering on the overall system performance of a loosely coupled GPS/INS system for aerospace applications. Both filter formulations were implemented and compared via Monte Carlo simulation runs with focus on the accuracy of the estimated inertial sensor biases and on GPS drop out situations.

We found a comparable performance of both navigation algorithms concerning attitude and position errors as well as inertial sensor bias estimation as long as GPS aiding was available. However, the simulation results indicate a superior performance of the direct Kalman filter formulation in GPS drop out situations, which can by explained by the way the inertial measurements are processed.

1 INTRODUCTION

An integrated navigation system exploits the complementary characteristics of different navigation sensors to increase the precision of the navigation solution. In addition, the resulting redundancy allows the detection of bad sensor data, which then can be rejected. Such an integrity monitoring increases the reliability of the navigation solution significantly. The navigation technique common to almost all integrated navigation systems is the inertial navigation. In a strapdown inertial navigation system (INS), an inertial measurement unit (IMU) mounted to the vehicle senses accelerations and angular rates for all six degrees of freedom of the vehicle. From these data, a strapdown algorithm (SDA) can compute a navigation solution presumed that initial position, velocity and attitude are known. This type of navigation is autonomous, therefore intentional or unintentional external jamming is impossible. Unfortunately, only short-term accuracy of the navigation solution is assured as the measurement errors of the inertial sensors sum up. Therefore, further navigation sensors such as global positioning system (GPS), terrain reference navigation (TRN) by baro-altimeter and radar-altimeter, and image based navigation (IBN) by IR seekers are used to aid the INS and to assure the long-term accuracy of the navigation solution. The data fusion of these different sensors is commonly accomplished by a Kalman filter [1],[2]. The performance of the Kalman filter is crucial to overall system performance, especially when low-cost sensors are integrated. This paper focusses on filtering GPS and IMU data.

In the classical way of aiding the INS, which is considered here for reference purposes, an indirect Kalman filter formulation is chosen. The Kalman filter estimates the errors of the SDA state vector, which can be corrected subsequently. The development of this design took place when due to limited computational ressources, the computational efficiency of the algorithm was of superior importance [3]. In a direct Kalman filter formulation, total quantities like position and velocity are estimated. As it is considered to be computationally more demanding, this design was commonly used only for alignment and calibration tasks and applications in which only slow dynamics were involved [4]. However, as CPU clock speeds are increasing, the computational cost of the algorithms used in an integrated navigation system is becoming less important.

This paper describes in detail both approaches to design Kalman filters for the data fusion task in integrated navigation systems. In the next section, the navigation equations are introduced. In Section three, indirect and direct Kalman filter formulations are described. In Section four, an alternative direct formulation with a computational efficiency comparable to the indirect formulation is derived. In Section five, simulation results are given. Finally, conclusions are drawn.

2 THE NAVIGATION EQUATIONS

The navigation equations are important for both the SDA and the Kalman filter. In the SDA, these differential equations are integrated to keep track of position, velocity and attitude of the vehicle. For the indirect Kalman filter formulation, the navigation equations are used to derive the error propagation equations by means of a Taylor series expansion which is truncated after the linear part. The error propagation equations represent the system model according to which the indirect Kalman filter is designed. For the direct Kalman filter, the navigation equations represent the nonlinear system the filter has to observe. The investigations presented in this paper were carried out using the navigation equations in a navigation frame (n-frame) mechanisation. The axes of the n-frame are given by the directions north, east and down. The down axis is parallel to the local gravity vector, which is the sum of the gravitational acceleration and the centripetal acceleration caused by the rotation of the earth. The n-frame as well as the body-fixed coordinate frame (b-frame) have their origins at the location of the navigation system. The axes of the b-frame are aligned with the roll, pitch and yaw axes of the vehicle. In the SDA, the attitude information was represented using a quaternion [5] in order to avoid singularities that can occur when Euler angles are used.

The continuous form strapdown inertial navigation equations are given by following set of nonlinear differential equations[6]:

$$\frac{\partial \vec{q}}{\partial t} = \frac{1}{2}\vec{q} * \left(0, \vec{\omega}_{ib}^b - C_n^b \left[\vec{\omega}_{ie}^n + \vec{\omega}_{en}^n\right]\right) \quad (1)$$

$$\frac{\partial \vec{v}_e^n}{\partial t} = C_b^n \vec{f}_{ib}^b - (2\vec{\omega}_{ie}^n + \vec{\omega}_{en}^n) \times \vec{v}_e^n + \vec{g}_l^n \quad (2)$$

$$\frac{\partial L}{\partial t} = \frac{v_{e,\mathrm{north}}^n}{R_n + h} \quad (3)$$

$$\frac{\partial \lambda}{\partial t} = \frac{v_{e,\mathrm{east}}^n}{(R_e + h)\cos(L)} \quad (4)$$

$$\frac{\partial h}{\partial t} = -v_{e,\mathrm{down}}^n \quad (5)$$

Herein denotes

$\vec{q}$	attitude quaternion
$*$	quaternion multiplication
C_b^n	Direction cosine matrix that transforms a vector from its b-frame component form to its n-frame component form, computed from $\vec{q}$.
$\vec{f}_{ib}^b$	specific force acceleration
$\vec{\omega}_{ib}^b$	angular rate of the b-frame with respect to a nonrotating inertial frame (i-frame), given in b-frame component form
$\vec{\omega}_{ie}^n$	angular rate of a coordinate frame with one axis parallel to the Earth's polar axis and the other axes fixed to the Earth (e-frame) with respect to the i-frame, given in n-frame component form
$\vec{\omega}_{en}^n$	angular rate of the n-frame with respect to the e-frame, given in n-frame component form
$\vec{v}_e^n$	velocity in north, east, and down direction with respect to the Earth, given in n-frame component form
L, λ, h	lattitude, longitude, height
R_n, R_e	Earth's meridian, and transverse radius of curvature.
$\vec{g}_l^n$	local gravity vector in n-frame component form

The IMU and the SDA which integrates (1)-(5) using the currently available angular rate and specific force measurements form the INS. Without any further aiding, the error in the computed position provided by the INS grows with second or even third order of time, respectively. In this contribution only loosely coupled systems are considered: it is assumed that the long-term accuracy of the navigation solution is assured by aiding the INS with the position information provided by a GPS receiver. The data fusion of INS and GPS can be accomplished using different Kalman filter formulations, which are described in the next section.

3 INDIRECT AND DIRECT KALMAN FILTER FORMULATION

3.1 Indirect Formulation

For the indirect Kalman filter formulation in which the errors of the SDA are estimated, the error propagation equations are needed. The equations for the position and velocity errors follow from (2)-(5). These nonlinear equations can be written in the following form:

$$\frac{\partial \vec{x}}{\partial t} = \vec{f}(\vec{x}) \tag{6}$$

Expanding Eq. (6) into a Taylor series and neglecting higher order terms leads to

$$\frac{\partial \vec{x}}{\partial t} \approx \vec{f}(\vec{x})|_{\vec{x}=\vec{x}_{\mathrm{SDA}}} + \frac{\partial \vec{f}(\vec{x})}{\partial \vec{x}}|_{\vec{x}=\vec{x}_{\mathrm{SDA}}} \cdot (\vec{x} - \vec{x}_{\mathrm{SDA}}) \tag{7}$$

where $\vec{x}_{\mathrm{SDA}}$ denotes the state of the SDA. Rearranging Eq. (7) gives the error propagation equations

$$\frac{\partial \Delta\vec{x}}{\partial t} = \frac{\partial \vec{f}(\vec{x})}{\partial \vec{x}}|_{\vec{x}=\vec{x}_{\mathrm{SDA}}} \Delta\vec{x} \tag{8}$$

where

$$\Delta\vec{x} = \vec{x} - \vec{x}_{\mathrm{SDA}}. \tag{9}$$

The attitude error propagation equations cannot be derived from (1) directly. As the attitude errors are considered to be small, they are commonly described using Euler angles. It is shown in [7] that the attitude errors propagate according to

$$\frac{\partial \Psi}{\partial t} = -\vec{\omega}_{in}^{n} \times \Psi - C_b^n \delta\vec{\omega}_{ib}^{b} + \delta\vec{\omega}_{in}^{n} \tag{10}$$

where Ψ is a vector containing the attitude errors in form of Euler angles, $\vec{\omega}_{in}^{n}$ is the angular rate of the n-frame with respect to an inertial frame given in n-frame component form, $\delta\vec{\omega}_{ib}^{b}$ are the angular rate sensor biases and $\delta\vec{\omega}_{in}^{n}$ are the errors in the n-frame rate estimates.
The linear system model, of which the discrete equivalent was used in the indirect Kalman filter formulation, is given by adding a zero-mean white gaussian noise process $\vec{w}$ multiplied with an appropriate input matrix G to the position, velocity and attitude error propagation equations. This model was augmented by six additional states to allow the estimation of time-constant or slowly varying angular rate sensor and accelerometer biases. The structure of the resulting fifteen-state linear system model can be seen from Eqs. (11) - (13).

$$\frac{\partial \Delta\vec{x}}{\partial t} = A\Delta\vec{x} + G\vec{w} \tag{11}$$

$$\Delta\vec{x} = \begin{pmatrix} \Delta\vec{x}_{\mathrm{ned}} \\ \Delta\vec{v}_{\mathrm{ned}} \\ \Psi \\ \delta\vec{f}_{ib}^{b} \\ \delta\vec{\omega}_{ib}^{b} \end{pmatrix}, \; G\vec{w} = \begin{pmatrix} 0 & 0 \\ C_b^n & 0 \\ 0 & C_b^n \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \vec{w}_{\mathrm{Acc}} \\ \vec{w}_{\mathrm{Gyro}} \end{pmatrix} \tag{12}$$

$$A = \begin{pmatrix} A_{11} & I & 0 & 0 & 0 \\ A_{21} & A_{22} & A_{23} & C_b^n & 0 \\ A_{31} & A_{32} & A_{33} & 0 & C_b^n \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{13}$$

Herein I denotes the 3×3 unity matrix and 0 denotes a 3×3 matrix containing only zeros. Finally, the measurement model which is needed to process the position information provided by a GPS receiver is given by

$$\Delta\vec{z}_k = H\Delta\vec{x}_k + \vec{\nu}_k \tag{14}$$

where

$$H = \begin{pmatrix} 1 & 0 & 0 & ... & 0 \\ 0 & 1 & 0 & ... & 0 \\ 0 & 0 & 1 & ... & 0 \end{pmatrix} \tag{15}$$

and $\vec{\nu}_k$ is a zero-mean, white gaussian noise sequence. When GPS data is available at timestep k, the errors of the SDA can be estimated by applying

$$\Delta\vec{x}_k^{+} = \Delta\vec{x}_k^{-} - K_k(H\Delta\vec{x}_k^{-} - \Delta\vec{z}_k) \tag{16}$$

where

$$\Delta\vec{z}_k = \begin{pmatrix} (L_{\mathrm{SDA}} - L_{\mathrm{GPS}})(R_n + h_{\mathrm{SDA}}) \\ (\lambda_{\mathrm{SDA}} - \lambda_{\mathrm{GPS}})(R_e + h_{\mathrm{SDA}})\cos(L_{\mathrm{SDA}}) \\ h_{\mathrm{SDA}} - h_{\mathrm{GPS}} \end{pmatrix}. \tag{17}$$

K_k denotes the Kalman gain matrix at timestep k, the superscripts $-$ and $+$ distinguish quantities before and after the measurement is processed, respectively. The subscripts SDA and GPS distinguish quantities provided by the SDA and the GPS receiver, respectively. With the estimated errors $\Delta\vec{x}$, the state of the SDA is corrected. In the indirect Kalman filter formulation described here, the time-consuming Kalman filter estimation step is only applied when GPS information is available. Accelerometer and angular rate sensor data enter the SDA directly after a correction by means of the estimated sensor biases. The noise of these sensors is therefore treated incorrectly as system noise. A simplified block diagram of the indirect Kalman filter formulation is shown in Fig. 1.

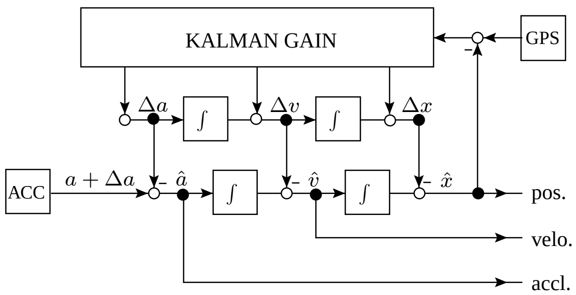

Figure 1: Simplified block diagram of the indirect Kalman filter formulation

3.2 Direct Formulation

In the direct Kalman filter formulation, total quantities like position, velocity and attitude are estimated directly, as these quantities are among the state variables of the filter. The nonlinear system model, according to which the filter is designed, is given by the navigation Eqs. (1)-(5). Furthermore, six states were added for the accelerations $\vec{f}_{ib}^b$ and the angular rates $\vec{\omega}_{ib}^b$ which were modeled as random constants. The model is completed by six states, which are needed to estimate the inertial sensor biases, and an appropriate input matrix G multiplied with a zero-mean, white gaussian noise process $\vec{w}$ to take into account model inadequacies, see Eq. (18)

$$\frac{\partial \vec{x}}{\partial t} = \vec{f}(\vec{x}) + G\vec{w} \tag{18}$$

The required linear system model is obtained by linearizing about the estimated state vector $\hat{\vec{x}}$:

$$F = \frac{\partial \vec{f}(\vec{x})}{\partial \vec{x}}\Big|_{\vec{x}=\hat{\vec{x}}} \tag{19}$$

The structure of the resulting twenty-two-state linear system model can be seen from Eqs. (20)-(22).

$$\frac{\partial \vec{x}}{\partial t} = F\vec{x} + G\vec{w} \tag{20}$$

$$\vec{x} = \begin{pmatrix} L, \lambda, h \\ \vec{v}_{\text{ned}} \\ \vec{f}_{ib}^b \\ \omega_{ib}^b \\ \vec{q} \\ \delta\vec{f}_{ib}^b \\ \delta\vec{\omega}_{ib}^b \end{pmatrix}, \; G\vec{w} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ I & 0 \\ 0 & I \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \vec{w}_1 \\ \vec{w}_2 \end{pmatrix} \tag{21}$$

$$F = \begin{pmatrix} F_{11} & F_{12} & 0 & 0 & 0 & 0 & 0 \\ F_{21} & F_{22} & C_b^n & 0 & F_{25} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ F_{51} & F_{52} & 0 & F_{54} & F_{55} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{22}$$

Again, I denotes the 3×3 unity matrix and 0 denotes 3×3 , 4×3, and 3×4 matrices containing only zeros. The measurement models which are needed to process the GPS receiver, angular rate sensor, and accelerometer data are straight forward, although an appropriate scaling of the GPS measurement matrix is necessary to assure the numerical stability of the algorithm. In opposite to the indirect Kalman filter formulation, all sensor data is processed in the estimation step of the filter. Therefore, all sensor noise is modeled correctly as measurement noise. The inherent disadvantage of this filter algorithm is its increased computational cost. This is due to the fact that the Kalman gain matrix has to be computed more frequently, which involves a time consuming matrix inversion. In the indirect Kalman filter formulation described previously, this computation is required only when a GPS measurement is available. Here the Kalman gain matrix has to be computed additionally when accelerometer and angular rate sensor measurements are available, which occur at a high rate. A simplified block diagram of the direct Kalman filter formulation is shown in Fig. 2.

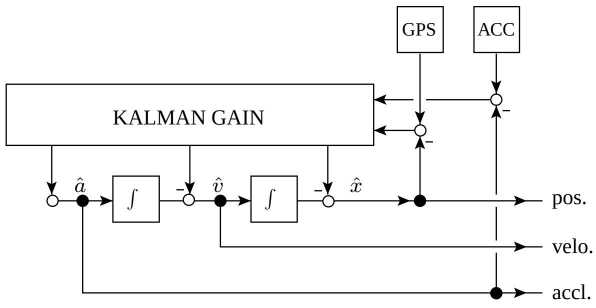

Figure 2: Simplified block diagram of the direct Kalman filter formulation

4 AN ALTERNATIVE DIRECT KALMAN FILTER FORMULATION

In order to avoid the increased computational cost caused by the processing of the inertial sensor data in the Kalman filter estimation step as in the algorithm described above, an alternative direct Kalman filter formulation was derived. The idea is to discard the state variables reserved for the angular rates $\vec{\omega}_{ib}^b$ and accelerations $\vec{f}_{ib}^b$. Instead, the inertial sensor measurements are treated as known input vector $\vec{u}$. This leads to the sixteen-state system model given by Eqs. (23)-(26).

$$\frac{\partial \vec{x}}{\partial t} = F\vec{x} + G\vec{u} + G\vec{w} \tag{23}$$

$$\vec{x} = \begin{pmatrix} L, \lambda, h \\ \vec{v}_{\text{ned}} \\ \vec{q} \\ \delta\vec{f}_{ib}^b \\ \delta\vec{\omega}_{ib}^b \end{pmatrix}, \quad G = \begin{pmatrix} 0 & 0 \\ C_b^n & 0 \\ 0 & F_{54} \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \tag{24}$$

$$\vec{u} = \begin{pmatrix} \vec{f}_{ib,\text{measured}}^b \\ \vec{\omega}_{ib,\text{measured}}^b \end{pmatrix}, \quad \vec{w} = \begin{pmatrix} \vec{w}_{\text{Acc}} \\ \vec{w}_{\text{Gyro}} \end{pmatrix} \tag{25}$$

$$F = \begin{pmatrix} F_{11} & F_{12} & 0 & 0 & 0 \\ F_{21} & F_{22} & F_{25} & -C_b^n & 0 \\ F_{51} & F_{52} & F_{55} & 0 & -F_{54} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{26}$$

The indexing of the submatrices in Eq. (26) is taken from Eq. (22), so that identical submatrixes receive the same index in both equations. The measurement model

Table 1: Characteristics of the sensors used for simulation

source	cycle time	noise
angular rate sensors	5 ms	$0.1\ {}^{\circ}/\sqrt{\mathrm{h}}$
accelerometers	5 ms	$0.05\ \mathrm{mg}/\sqrt{\mathrm{Hz}}$
GPS receiver	1 s	10 m

required to process the GPS receiver data is straightforward and nearly identical to the direct Kalman filter formulation described before. This algorithm offers a computational cost comparable to the indirect Kalman filter formulation. Unfortunately, the inertial sensor noise is treated incorrectly as system noise, too. A simplified block diagram of this alternative direct Kalman filter formulation is shown in Fig. 3.

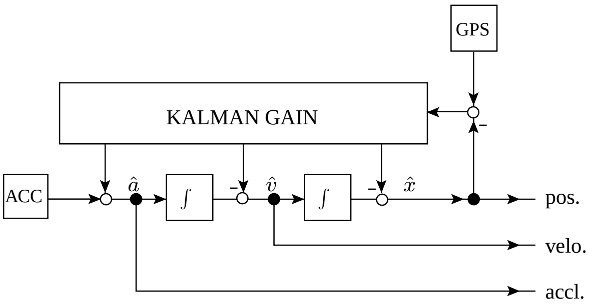

Figure 3: Simplified block diagram of the alternative direct Kalman filter formulation

5 SIMULATION RESULTS

The aim of the numerical simulations was to compare the performance of the different Kalman filter formulations described in the previous sections during a representative twenty-minute mission flight. Hypothetical inertial sensor and GPS receiver data was generated by corrupting the ideal values with white noise according to Table 1. In addition, constant accelerometer and angular rate sensor biases were assumed. At the 900 second point into the mission, a GPS outage lasting one minute was assumed.

As the initial values of the covariance matrix of the Kalman filter state have a significant influence on filter performance especially in the first few minutes after start of the mission, all corresponding values were initialized identically: The variances of the initial attitude errors of the indirect Kalman filter formulation given in terms of Euler angles were used to compute the initial variances of the quaternion coefficients of the two direct Kalman filter formulations. In the same way, the variances of latitude and longitude were initialized from the variances of the errors in north and east directions. With this procedure, the initial values of the state covariance matrix of the sixteen-state direct formulation were specified completely. For the twenty-two-state direct formulation, some degrees of freedom persisted.

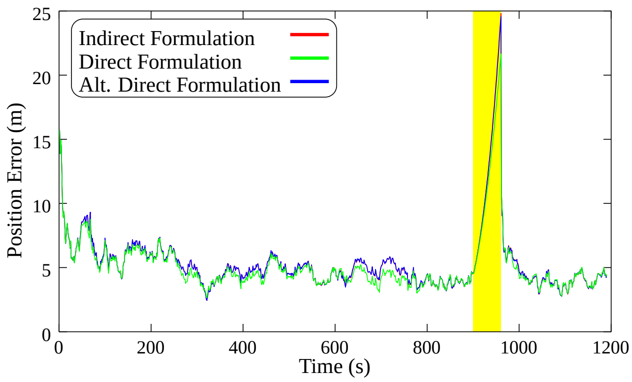

Figure 4: Position errors obtained with different Kalman filter formulations. (The red graph is covered almost completely by the blue one.)

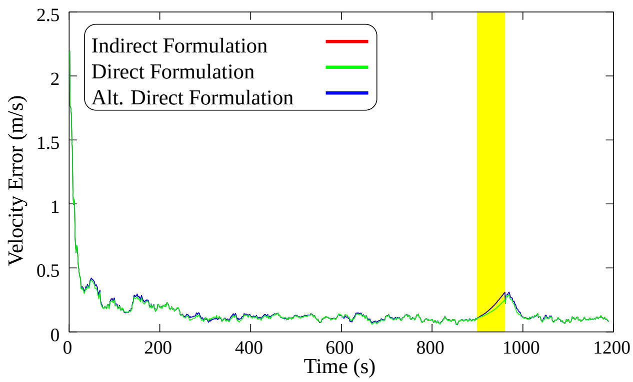

Figure 5: Velocity errors obtained with different Kalman filter formulations. (The red graph is covered almost completely by the blue one.)

Figures 4 to 6 show the averaged position, velocity and attitude errors of the different filters obtained by Monte Carlo simulation runs. The GPS outage is marked yellow. Although there are significant structural differences between the alternative direct and the indirect Kalman filter formulations shown in blue and red, respectively, the plots indicate an identical performance of these two filters. During the time when GPS-aiding is available, the direct formulation shows a performance comparable to the indirect and alternative direct formulation. However, in the case of GPS loss, the errors in position, velocity and attitude grow slower for the direct formulation. This advantage results from the processing of the inertial sensor data in the estimation step of the Kalman filter.

Based on appropriate system models, the Kalman filters are able to estimate the biases of the inertial sensors. Figures 7 and 8 show the biases estimated by the different filter formulations. The true biases that were added to the noisy inertial meassurements are shown in black. Again, the performance of the indirect and the alternative direct formulation is identical and comparable to the performance of the direct formulation.

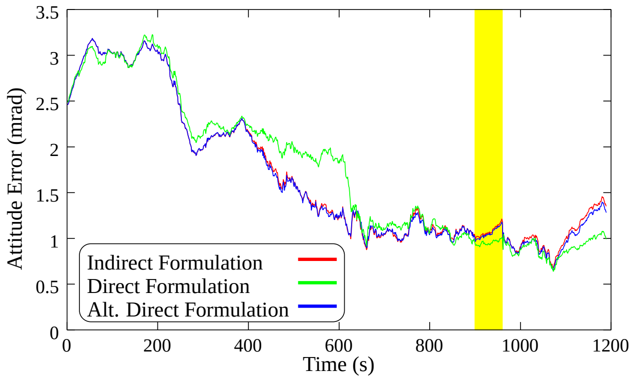

Figure 6: Attitude errors obtained with different Kalman filter formulations. (The red graph is covered almost completely by the blue one.)

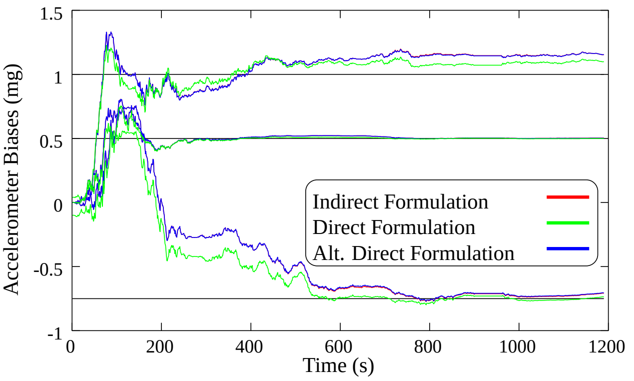

Figure 7: Estimation of accelerometer biases obtained with different Kalman filter formulations. (The red graphs are covered almost completely by the blue ones.)

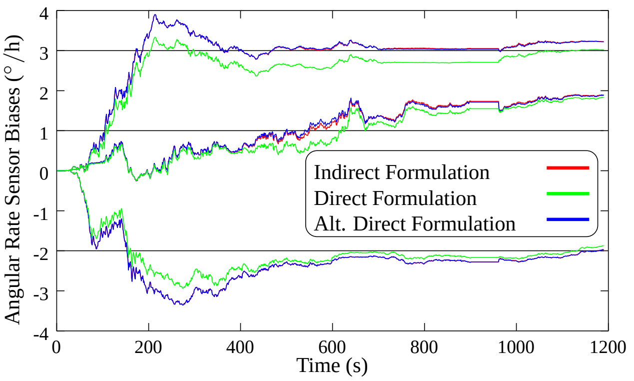

Figure 8: Estimation of angular rate sensor biases obtained with different Kalman filter formulations. (The red graphs are covered almost completely by the blue ones.)

6 CONCLUSION

In this paper, the design of different Kalman filters for the datafusion in integrated navigation systems was described. Simulation results indicate an identical performance of the widely used indirect formulation where the errors of the SDA are estimated, and the alternative direct formulation where total quantities like position, velocity and attitude are estimated directly. The direct formulation, which processes the inertial sensor data in the estimation step of the filter, offers better results in GPS drop out situations at the expense of an increased computational load.

Further work will be carried out to assess the robustness of these algorithms concerning unknown correlations and variances of the inertial sensor noise in the case of strong mechanical missile vibrations [8] as well as to extend the present systems to tightly coupled GPS/INS systems with additional aiding sensors.

REFERENCES

[1] Hutchinson, C. E.: *The Kalman Filter Applied to Aerospace and Electronic Systems*. IEEE Transactions on Aerospace and Electronic Systems, Vol.20, No.4, July 1984, pp.500-504.

[2] Gelb, A.(Editor): *Applied Optimal Estimation*. The M.I.T. Press - Fourteenth Printing, Cambridge, Massachusetts, and London, England 1996.

[3] Wagner, J., and Kasties, G.: *Aspects of Combining Satellite Navigation and Low-Cost Inertial Sensors* Symposium Gyro Technology, Stuttgart,Germany , 1996.

[4] Maybeck, P. S.: *Stochastic Models, Estimation and Control, Volume 1*. Academic Press, New York, 1979.

[5] Gupta, S.: *Linear Quaternion Equations with Application to Spacecraft Attitude Propagation* IEEE Aerospace Conference, Vol.1, 1998, pp.69-76.

[6] Titterton, D.H., and Weston, J.L.: *Strapdown Inertial Navigation Technology*. Peter Peregrinus Ltd., on behalf of the Institution of Electrical Engineers, London, England 1997.

[7] Britting, K.R.: *Inertial Navigation System Analysis* New York: Wiley-Intersciences, 1971.

[8] Wendel, J., and Trommer, G.J.: *Impact of Mechanical Vibrations on the Performance of Integrated Navigation Systems and on Optimal IMU Specification*. accepted for publishing at The ION 57th Annual Meeting & CIGTF's Guidance Test Symposium June 11-13, Albuquerque, New Mexico, USA, 2001.