 Scientific Technical Review, 2014,Vol.64,No.2,pp.14-20

UDK: 656.61.052:621.39
COSATI: 17-02, 17-07, 14-02

Adaptive Error Damping in the Vertical Channel of the Ins/Gps/Baro-Altimeter Integrated Navigation System

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In the inertial navigation system (INS), the altitude error diverges exponentially, especially in low-cost sensors. To suppress divergence of the altitude error, a Global Positioning System (GPS) receiver and a barometric altimeter (baro-altimeter) are utilized. This paper describes the error dumping of the vertical channel in the integrated navigation system INS/GPS and the baro-altimeter by using the 3rd order vertical channel damping loop and the application of the adaptive error damp coefficients. The integration is done with an extended Kalman filter (EKF) with control signals. The characteristics of the proposed model for the integration of the INS, the GPS and the baro-altimeter were analyzed by a computer simulation as well as experimentally, using a vehicle. The results of the analysis show that the navigation solutions of the INS/GPS/Baro-altimeter navigation system could improve the accuracywith the adaptive error control coefficients in the EKF control signal.

Key words: **inertial navigation, navigation system, global positioning system, barometric altimeter, kalman filters, error correction, algorithms.**

Introduction

AN inertial navigation system is an autonomous system for determining the position, velocity and attitude of an object using three linear accelerometers and three rate gyroscopes, [1]. In this paper, the "Strap-down" INS (SDINS) is used for analyzing and testing. The main characteristic of the low cost INS is its low accuracy. Weak points of these sensors are complex stochastic errors that are difficult to model, [2]. The vertical channel error diverges exponentially, so if the error is not dumped, the vertical data of the INS cannot be trusted during a long time period, [3].

The addition of baro-altimeters to integrated navigation systems is an already known idea, as they are typically inserted into INS systems to reduce error growth in the local vertical channel. The most widely used methods are a vertical channel damping loop (baro-inertial damping loop) and Kalman filter mechanization.

So far, many researchers have focused on INSs constructed with low cost sensors in order to improve their accuracy and reduce total costs of navigation systems, [4]. Jaewon et al. proposed an error compensation model for the INS vertical channel, where the well-known vertical channel damping loop is constituted, and then with a GPS and the loop, a Kalman filter for error compensation is designed, [3]. Salychev et al. used GPS data to correct the IMU, [5]. Kim J.H. et al. presented the results of improving an INS/GPS navigation system with a baro-altimeter for an Unmanned Aerial Vehicle [6]. The results showed that the INS/GPS/Baro-altimeter navigation system could provide a more reliable and accurate navigation solution under high maneuvering environments by using a ten-state Kalman filter to blend the INS optimally with a GPS and a baro-altimeter, [6]. Satheesh Readdy et al. have shown that the baro-altimeter data and the INS data fuse with a four state Kalman filter to obtain an accurate estimate of the flight altitude, [7]. Sokolovic et al. used a 2nd order vertical channel loop and an EKF with an adaptation of the vertical velocity component to improve the accuracy of the altitude, [8].

The aim of this work is to show that the application of the adaptive error (gain and damp) coefficients in the 3rd order vertical channel loop of the integrated navigation system improve the accuracy of the navigation solution by using different non-linear functions for the adaptations of the control signals introduced in the EKF filter.

Error model for the baro-altimeter

The measurement model of the baro-altimeter includes the bias error of the 1st order Markov process, the scale factor error of the random constant and white Gaussian noise [9], and is expressed in the next equation:

$$\begin{aligned} h_B &= h_T + \delta h_B = h_T + B + S h_T + v_B, \\ \dot{B} &= -\frac{1}{\tau} B + w, \\ \dot{S} &= 0, \end{aligned} \tag{1}$$

where, h_B is the measurement of the barometer, h_T is the true height, δh_B is the error component of the barometer output, B is the bias error, S is the scale factor error, v_B is the measurement noise, τ is the correlation time of the bias error, and w is driving white Gaussian noise for the bias error

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Damping of vertical channel errors in the ins

Vertical channel damping loop

The equation which describes the behavior of the SDINS vertical channels [8], given in the local NED coordinate system, can be written as:

$$\dot{V}_D = f_D - \left[\left(2\omega_e\cos\phi + \frac{V_E}{R_p + h}\right)V_E - \left(-\frac{V_N}{R_M + h}\right)V_N\right] + g_\phi(h), \qquad (2)$$

where: $\dot{V}_D = \dfrac{dV_D}{dt}$ - derivative of the vertical velocity component, V_N, V_E – component velocity towards the north and the east, f_D - specific force along the vertical axis, φ, h - latitude and altitude, $g_\phi(h)$ - vector of gravitational acceleration.

Based on the above equation to ensure the stability of the vertical channels, an external source of information about the altitude (barometric altimeter) is used, the measurements of which are independently filtered, [10].

The vertical channel damping loop is a system that suppresses the divergence of the vertical channel error and makes the height information calculated by the INS valid. It is classified into 1st order, 2nd order and 3rd order vertical channel damping loops and it uses the output of the non-inertial aiding sensor as a reference input. In this paper, the 3rd order loop is used [11], and its structure is given in Fig.1.

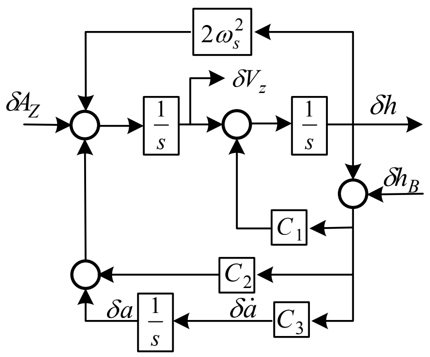

Figure 1. Error model of the 3rd order vertical channel damping loop.

The purpose of the loop is to drive the error δh towards 0. Withexternal information of the altitude and on the basis of Fig. 1, the error model in the vertical channel can be described as

$$\begin{aligned} \delta\dot{h} &= \delta V_Z - C_1(\delta h - \delta h_B), \\ \delta\dot{V}_Z &= \delta A_Z - C_2(\delta h - \delta h_B) - \delta a + 2\omega_s^2\delta h, \\ \delta\dot{a} &= C_3(\delta h - \delta h_B), \end{aligned} \qquad (3)$$

where δV_Z is the velocity error, δh is the error component of the INS measurement height, δA_Z is the error of the vertical acceleration measurement, δa is the output of the compensator of the feedback loop which eliminates the steady state error of the shown system, ω_s is Shuler's frequency, and C_1, C_2 and C_3 are control gains or control coefficients of the instability of the vertical channel error.

The gains C_1, C_2, C_3 are selected in such a way that they yield the least square response of the loop to the white noise inputs; these gains are in fact the steady-state Kalman gains, and can be analytically determined as explained by Brown, R.G., and Hwang, P.Y.C, [11].

The characteristic equation of this loop in Fig.1 is:

$$s^3 + C_1 s^2 + (C_2 - c)s + C_3 = 0, c = 2g_0 / R_0 . \qquad (4)$$

The loop will be stable provided that C_1 is positive and C_2 greater than $2g/R_0$, [12]. For the real poles of the system at $s = -\frac{1}{\tau}\left[\left(s^2 + \frac{1}{\tau}\right)^2 = 0\right]$, the coefficients are defined as, [13],

$$C_1 = \frac{3}{\tau}, C_2 = \frac{3}{\tau^2} + 2\frac{g_0}{R_0}, C_3 = \frac{1}{\tau^3} . \qquad (5)$$

The equations of GPS and baro-altimeter measurements are defined as:

$$\begin{aligned} m_{GPS} &= h - h_{GPS} = \begin{bmatrix}1 & 0 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}\delta h \\ \delta V_Z \\ \delta a \\ B \\ S\end{bmatrix} + \nu_{GPS}, \\ m_{baro} &= h - h_{baro} = \begin{bmatrix}1 & 0 & 0 & -1 & -h_T\end{bmatrix}\begin{bmatrix}\delta h \\ \delta V_Z \\ \delta a \\ B \\ S\end{bmatrix} + \nu_B, \end{aligned} \qquad (6)$$

where h_{GPS} is the measurement of the GPS and ν_{GPS} is the measurement noise of the GPS.

Adaptation of the gain and damp coefficients

Based on the previous research, the appropriate coefficients C_1, C_2 and C_3 for the INS vertical channel corrections are used. These coefficients for the INS error correction could be increased for better error damping. However, high values of the gain and damp coefficients can cause system instability [9]. Therefore, in this model of integration, separation of these coefficients has been made, introducing C_1, C_2, C_3 as coefficients for the INS correction, and C_{1KF}; C_{2KF}; C_{3KF} for an EKF implementation purpose, where $C_3 = C_{3KF}$. Fig.2 shows the scheme of the separation and adaptation of the gain and damp coefficients.

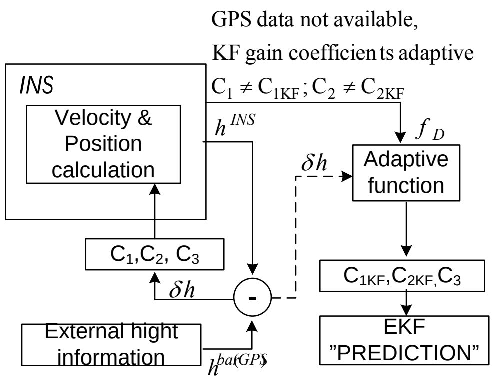

Figure 2. Separation of the gain and damp coefficients.

When there are no valid GPS measurements, the EKF performs prediction, based on the covariance matrices **Q** (system noise) and **R** (measurement noise). During the period of prediction, damping of altitude and vertical velocity errors is done by using the external sensor (baro-altimeter) which requires higher values of the gain and damp coefficients. For this reason, the adaptation of the values of C_{1KF}; and C_{2KF}, is done during the period when there are no GPS data, in accordance with the current IMU measurements. The optimal choice of the coefficients C is based on a compromise between the size of the system static errors and the required system bandwidth relative to the high-frequency components of the errors.

As some simulations will show, the existence of the vertical acceleration of the object during the period when the GPS is not in use significantly reduces the accuracy of the navigation solution. The damping coefficients have been defined according to the current value of the altitude error, using the nonlinear functions (tanh(bx) and sinh(bx)). The attenuation of the errors in the vertical channel, based on (3), by using the adaptive coefficients, is described as:

$$\begin{aligned} &\delta\dot{h} = \delta V_Z - C_{1KF}\tanh(b(\delta h - \delta h_B)), \\ &\delta\dot{V}_Z = \delta A_Z - C_{2KF}\tanh(b(\delta h - \delta h_B)) - \delta a + 2\omega_s^2\delta h, \\ &\delta\dot{a} = C_{3KF}(\delta h - \delta h_B). \end{aligned} \quad (7)$$

Extended kalman filter

Based on the equations for the INS attitude [14] and the horizontal and vertical channel error model [15], the form of the EKF is:

$$\dot{\mathbf{x}} = \mathbf{F}\cdot\mathbf{x} + \mathbf{G}\cdot\mathbf{w}, \quad (8)$$

where the matrices **F** and **G** have been formed based on the above mentioned errors models for the INS. The state vector is given as:

$$\mathbf{x} = \\ = \begin{bmatrix} \delta r_N & \delta r_E & \delta r_D & \delta V_N & \delta V_E & \delta V_D & \delta\varphi & \delta\theta & \delta\psi & B_N & B_E & B_D & \omega_N^{dr} & \omega_E^{dr} & \omega_D^{dr} \end{bmatrix} \quad (9)$$

The state transition matrix $\mathbf{\Phi}$ is:

$$\mathbf{\Phi}_k = \mathbf{I} + \mathbf{F}\Delta t + \frac{1}{2}\mathbf{F}^2(\Delta t)^2, \quad (10)$$

where Δt is a sampling period. The measurement model is:

$$\mathbf{z_k} = \mathbf{H_k}\cdot\mathbf{x_k} + \mathbf{v_k}, \quad (11)$$

with ones and zero values in $\mathbf{H}_k$, where the vector $\mathbf{v_k}$ represents Gaussian measurement noise. The error states estimated and predicted by the EKF are given as [16],

$$\hat{\mathbf{x}}_\mathbf{k}^+ = \mathbf{\Phi_k}\hat{\mathbf{x}}_\mathbf{k-1}^+ + \mathbf{L}\mathbf{u_k} + \mathbf{K_k}(\mathbf{z_k} - \mathbf{H_k}\mathbf{\Phi_k}\hat{\mathbf{x}}_\mathbf{k-1}^+ - \mathbf{H_k}\mathbf{L}\mathbf{u_k}), \quad (12)$$

where: **L** is a matrix consisting of zeros and ones, and **u** is a vector consisting of control signals:

$$\mathbf{u_{k-1}} = \begin{bmatrix} 0 & 0 & u_D^r & 0 & 0 & u_D^v \end{bmatrix}. \quad (13)$$

The Kalman gains matrix $\mathbf{K_k}$ is defined as:

$$\mathbf{K_k} = \mathbf{P_k^-}\mathbf{H^T}\left[\mathbf{H}\mathbf{P_k^-}\mathbf{H^T} + \mathbf{R_k}\right]^{-1}, \quad (14)$$

but when there are no GPS measurements, the gain matrix is not calculated but formed as a zero matrix (**K** = 0) at each step of calculation.

The state covariance matrices are:

$$\begin{aligned} &\mathbf{P_k^-} = \mathbf{\Phi_k}\mathbf{P_{k-1}^-}\mathbf{\Phi_k^T} + \mathbf{G_k}\mathbf{Q_k}\mathbf{G_k^T}, \\ &\mathbf{P_k^+} = (\mathbf{I} - \mathbf{K_k}\mathbf{H})\mathbf{P_k^-}, \end{aligned} \quad (15)$$

while $\mathbf{Q_k} = E\left[w_k w_k^T\right]$, is a covariance matrix of the system noise. The control signals u_D^r and u_D^v are defined as:

$$\begin{aligned} &u_D^r = -C_{1KF}\tanh(b_1\cdot\delta h), u_D^v = \\ &= -C_{2KF}\tanh(b_2\cdot\delta h) - C_{3KF}(\delta h)\Delta t, \\ &\text{or} \\ &u_D^r = -C_{1KF}\sinh(b_1\cdot\delta h), u_D^v = \\ &= -C_{2KF}\sinh(b_2\cdot\delta h) - C_{3KF}(\delta h)\Delta t. \end{aligned} \quad (16)$$

The altitude and vertical velocity values are corrected with the estimates of the altitude and velocity errors:

$$\begin{aligned} &h^c = h^{ins} - \delta\hat{h}, \\ &V_D^c = V_D^{ins} - \delta\hat{V}_D, \end{aligned} \quad (17)$$

Simulation

The simulation is done in two cases (two adaptive functions), under the same conditions shown in Table 1.

Table 1. The simulation conditions.

Sensor	Error type	Value
Accelerometer	Measurement noise (1 σ)	0.05 m/s^2
	Bias	0.0001 m/s^2
GPS	Position measurement noise (1 σ)	0.05m
	Position bias	0.0001m
	Velocity measurement noise (1 σ)	0.001 m/s
	Velocity bias	0.00001 m/s
Baro-altimeter	Measurement noise (1 σ)	1 m
	Bias	0.05 m

The INS vertical channel is constituted by the proposed method in section 3, and its performance is analyzed by Monte Carlo simulation, in 100 iterations. The mean square of the vertical channel error of the proposed model is compared with that of the conventional model. The Kalman filter is implemented as an EKF based on the error models for INS sensors equations and mechanization equations for a loosely coupled GPS/INS integration, [16]. For the error compensation analysis purpose, the altitude profile and the results of the baro-altimeter sensor error measurements are shown in Fig.3. The trajectory was chosen to show the results

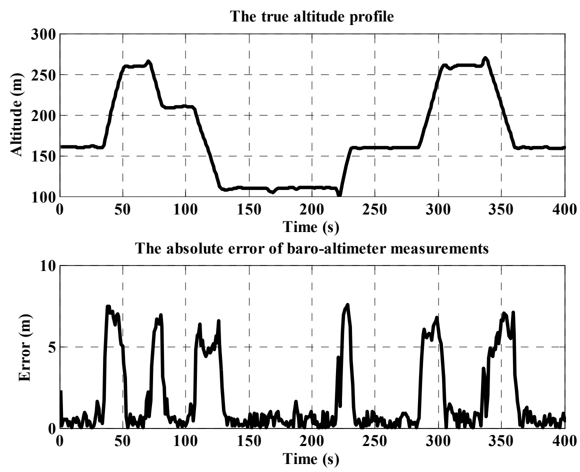

Figure 3. The altitude profile and the results of the baro-altimeter sensor error measurements

for the cases of high and low vertical maneuvers, which affects the appearance of higher or lower errors in the navigation solution (altitude and velocity in the downward direction). The aiding device has stable characteristics but is unable to capture fast changes in the altitude when the platform climbs or dives or in the presence of significant vertical acceleration, whereas the height measured by the INS is unstable and need to be bounded by an external aiding sensor as a reference. The C_1, C_2 and C_3 coefficients have to be chosen so that the resulting h contains both the stable characteristics of the aiding sensor and the high dynamics of the altitude, calculated on the basis of the INS measurements.

A proper selection of high values of C_{1KF} - C_{3KF} provides small static errors, but the system has a wide bandwidth and poor damping of high frequency noise and vice versa, [17]. In accordance with this, Fig.4 shows the control signals for the altitude and vertical velocity error damping.

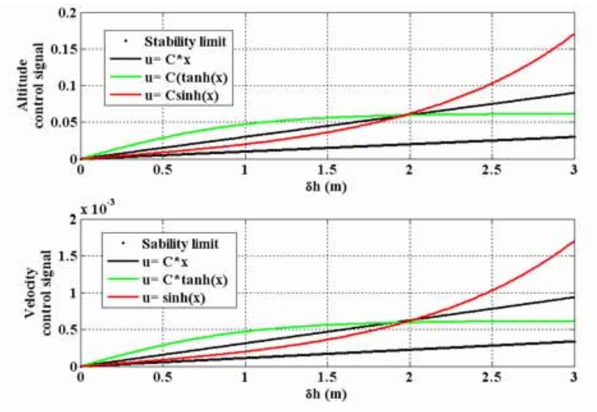

Figure 4. The altitude and vertical velocity control signals.

Kalman gains are, by definition, time varying, and they reach steady state when equilibrium occurs between process noise variance accumulation and measurement noise variance; these steady-state gains in the Kalman filter are the same as the optimum C_1, C_2, C_3 gains used for error damping in the SDINS. The adaptation of these coefficients is done only when GPS data are not available.

The characteristic equation (4) is not different from the one obtained by linearizing sinh(.) and tanh (.) and it is the same as Eq. (5.80), Rogers, [9]. The gains in Eq. (5) are obtained as in Sec. 5.6.1, Eqs. (5.81)-(5.83), Rogers, [9]. The gains are somewhat different because of different choices of the closed-loop eigenvalues. Therefore, the values of the coefficients C_{1KF} and C_{2KF} have to be defined under the condition of (4) and (5) and they have been chosen based on the maximum expected value of the altitude difference between the INS and the external measurement sensor, which was 2m in the simulation case.

The problem in the implementation of the adaptive function tanh () is that, as input error values become higher, the function response increases quickly and reaches saturation. When compared to the function tanh (), the function sinh () is defined in a wider domain of input values, and as the input signal error values become higher the function response increases slowly for small inputs (almost a linear characteristic)while it increases quickly for higher values. This characteristic of the function sinh () allows an easier set of appropriate error gain and damp coefficients in order to achieve better damping of altitude and velocity errors, as it is shown in Fig. 4.

The error gain and damp coefficients that have been chosen in the simulation are C_1= 0.03, C_2 = 3.124×10^{-4} and C_3 = 1.2×10^{-6} when GPS data are available and C_{1KF}=0.06, C_{2KF}=6.2×10^{-4}, and C_{3KF} =1.2×10^{-6} for $u = C\times tanh(x)$; and C_{1KF}=0.017, C_{2KF} = 2×10^{-4}, and C_{3KF} = 1.2×10^{-6} for $u = C \times sinh(x)$.

Fig.5 and 6 show the estimated values of the altitude and the velocity for the two previous cases respectively, based on the models for error damping with constant and adaptive coefficients.

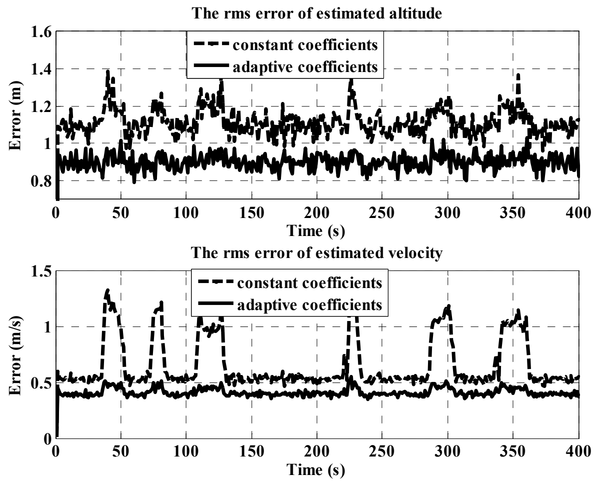

Figure 5. The rms error of the estimated values of the altitude and the velocity with constant and adaptive values of the gain and damp coefficients (adaptation with the function tanh()).

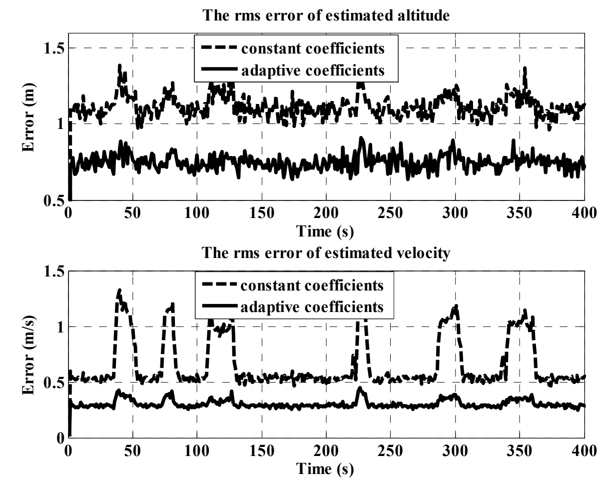

Figure 6. The rms error of the estimated values of the altitude and the velocity with constant and adaptive values of the gain and damp coefficients (adaptation with the function sinh()).

Fig.5 and 6 show that the errors of the estimated altitude and the velocity are lower when the error damping is done with adaptive coefficients. It can be seen that the error of the estimated altitude and the estimated velocity is the highest during the maneuver of the platform, more precisely when there is a linear acceleration of the platform and vice versa. The comparison of the results of these two cases is shown in Fig.7.

The results in the Figureclearly show that better results were obtained using the adaptive function sinh(), both in the linear movement of the platform and during the vertical maneuver. Based on the results of the estimated altitude and velocity given in Table 2, it can be concluded that the results are better in the case of error damping with adaptive coefficients than with constant coefficients and particularlywhen the adaptation is done by using the function sinh().

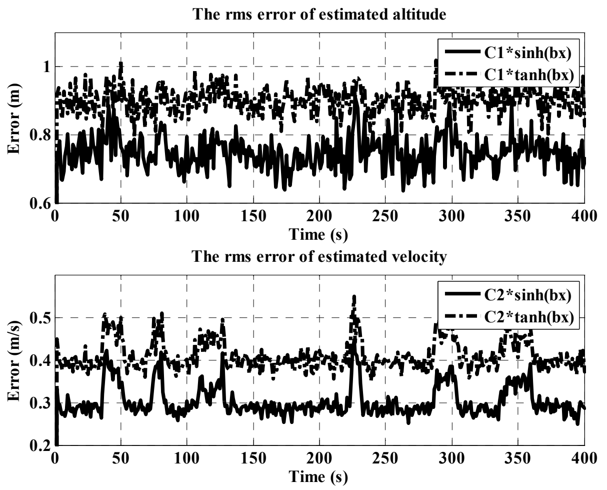

Figure 7. Comparative presentation of the results (rms) achieved by using the adaptive coefficients (adaptation with the functions sinh() and tanh()).

Table 2. Summary of the simulation results.

Case N°		Constant coefficients			Adaptive coefficients tanh()/sinh()		
		max	min	rms	max	min	rms
1	Altitude (m)	4.49	- 3.7	1.11	3.28/ 2.75	- 3.1/ - 2.5	0.91/ 0.78
	Velocity (m/s)	3.09	- 2.37	0.66	3.11/ 2.8	- 2.9/ - 1.8	0.43/ 0.31

Experimental verification of the integrated system

In this work, the SDINS consists of MEMS low cost sensors the MPU-60X0 which is the integrated 6-axis MotionTracking device that combines a 3-axis gyroscope and a 3-axis accelerometer. A GPS receiver is of a "Gms-u1LP" type (L1 C/A code, updating frequency 10 Hz). The barometric pressure sensor is MS5611-01BA03.

The biases and scale factor errors of inertial sensors and the platform orientation errors are used from product specifications. These data are used for inertial sensor calibration and the initialization of the covariance matrices of the EKF. The estimation of sensors' stochastic models has been done using Allan dispersion and the autocorrelation function when the dispersions of separate noise components are determined.

The experiment was conducted on a vehicle with installed sensors. The vehicle moved along a pre-defined path. During the test time, the system worked in the initialization regime for 6 min and in the navigation regime for 5 min. The analyses were done after data collection, when the periods of GPS absence were introduced intentionally, for the post processing analyses. During the GPS unavailability, (839 - 850 s and 860 - 885 s (injected for the test only)) the EKF worked in the prediction mode. The gain and damp coefficients in this model were $C_1 = 0.04$, $C_2 = 0.8$ and $C_3 = 1.25\times10^{-6}$, $C_{1KF} = 0.035$, $C_{2KF} = 3.2\times10^{-4}$ and $C_3 = 1.25\times10^{-6}$, based on the maximum expected value of the altitude difference of 1.25m.

Fig.8 illustrates the absolute error of a part of the altitude and the down velocity profile, obtained with constant and adaptive values of the gain and damp coefficients. From the graph shown in Fig. 8it can be seen that the deviations of the estimated values of the altitude and velocity are smaller after the coefficient adaptation. Table 3 summarizes the quantitative results of the experiment (min value, max value, and root mean square errors (rms) related to the estimated and true altitude and velocity).

The results in Fig.8 show that the model with the adaptive error damping is resilient to sudden occurrence of errors compared to the model with the constant coefficients. This is particularly noticeable at the time points around 845 s.

It is also obvious that, during the periods from 860 s to 885 s, the results obtained with adaptation are more accurate than in the case of linear correction, (see also T able 3), compared to the true values of the altitude and the vertical velocity of the vehicle.

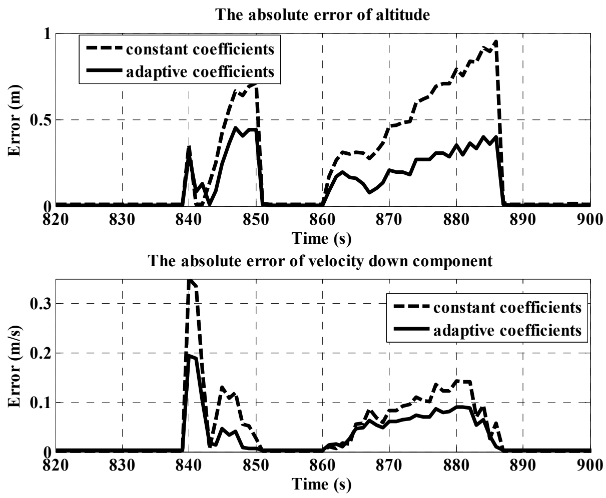

Figure 8. The absolute error of the estimated altitude and velocity (down component) of the vehicle test trajectory.

Table 3. Summary of the experimental results.

	Constant coefficients			Adaptive coefficients		
	max	min	rms	max	min	rms
Altitude (m)	0.75	- 0.95	1.114	1.38	- 0.45	0.32
Velocity (m/s)	0.13	- 0.35	0.035	0.05	- 0.2	0.025

Conclusion

This paper presents a multi-sensor INS/GPS/Baro-altimeter integrated navigation system. The main goal of this research was to adapt the error gain and damp coefficients in the 3rd order vertical channel damping loop in order to improve the altitude and the vertical velocity accuracy by using the EKF with a control signal. The adaptation of the coefficients was done with non-linear functions and the results for the proposed model are analyzed based on the simulation and experimental results. It is concluded that the proposed model for error damping in the vertical channel of the integrated navigation system improves the accuracy of navigation solutions, particularly when there are no valid GPS measurements. It is also shown that better results can be achieved with the usage of the adaptive function sinh() than with the adaptive function tanh(). The results obtained from the proposed model for error dumping have also shown that the proposed model is resistant to sudden occurrence of errors incurred during the vertical maneuvering of the object.

Acknowledgement

The results presented in this paper are obtained within the project "Profitable choice of new technologies and concepts of defense through social changes and strategic orientation of

Serbia in the 21st century", No III 047029, financed by the Ministry of Science and Technology Development, the Republic of Serbia (2010.-2014.).

References

[1] ZHANG,P.; GU,J.; MILIOS,E.E., HUYNH,P.: *Navigation with IMU/GPS/Digital Compass with unscented kalman filter*, In Proceedings of the IEEE International Conference on Mechatronics & Automation, Niagara Falls, Canada, 2005.

[2] BISTROVS,V., KLUGA,A.: *MEMS INS/GPS data fusion using particle filter. Electronics and Electrical Engineering*, 2011, Vol.112, No.6, pp.77-80.

[3] SEO,J.; LEE,J.G., PARK,C.G.: *A New error compensation scheme for INS vertical channel*, In 16th IFAC Symposium on Automatic Control in Aerospace. Saint-Petersburg, Russia, 14-18 June 2004.

[4] ASANOVIĆ,N., TRAJKOVSKI,I., VUKMIRICA,V., STANOJKOVIC,S.: *Realization of inertial navigation system on flight computer for unmanned aerial vehicle*, Scientific Technical Review, ISSN 1820-0206, 2011, Vol.61, No.3-4, pp.16-24.

[5] SALYCHEV, O. S.; VORONOV, V. V.; *Cannon, M. E. & Lachapelle, G. Low cost INS/GPS integration: concepts and testing*, In Proceedings of the Institute of Navigation, National Technical Meeting. Anaheim, CA, January 2000, pp. 98–105.

[6] KIM,J.H. SUKKARIEH,S.: *A baro-altimeter augmented INS/GPS navigation system for an uninhabited aerial vehicle*, In SatNav 2003, the 6th International Symposium on Satellite Navigation Technology Including Mobile Positioning & Location Services, Melbourne, Australia, 22-25 July 2003.

[7] READDY,G.S., SARASWAT,V.K.: *Advanced Navigation System for Aircraft Applications*, Defence. Sci. J., 2013, Vol.63, No.2, pp.131-137.

[8] SOKOLOVIC,V.: DIKIC,G., STANCIC,R.: *Integration of INS*, GPS, Magnetometer and Barometer for Improving Accuracy Navigation of the Vehicle. Defence. Sci. J., 2013, Vol.65, No.5, pp.451-455.

[9] ROGERS,R.M.: *Applied Mathematics in Integrated Navigation Systems*, American Institute of Aeronautics and Astronautics, 3rd edition, 2007.

[10] DADUC,V., REDDYA,B.V., SITARAA,B., CHANDRASEKHARA,R.S., REDDYA,G.S.: *Baro-INS integration with kalman filter. In Proceedings of National Conference on Advances in Sensors for Aerospace Applications*, Hyderabad, December 2007.

[11] BROWN,R.G., HWANG,P.Y.C.: *Introduction to Random Signals and Applied Kalman Filtering*, J. Wiley, 1997, 3rd ed, pp.132-134.

[12] DORF,R.C., BISHOP,R.H.: *Modern Control Systems*, Addison-Wesley, 1995.

[13] HAERHEE,P., WON-SANG,R., IEK-HO,W.: *Robust Complementary Filter Design and its Application to GPS/INS vertical channel design*, In Proceedings of International Conference on Electrical Engineering, Yong Pyong Resort, Korea 9-13 July 2006.

[14] AHMED,M.S., ĆUK,D.: *A new integrated GPS/INS method*, Scientific Technical Review, ISSN 1820-0206, 2006, Vol.56, No.1, pp.3-13.

[15] TITERTON,D.H., WESTON,J.L.: *Strapdown inertial navigation technology*, 2nd ed. The Institution of Electrical Engineers, Herts, UK, 2004.

[16] STANCIC,R., GRAOVAC,S.: *The integration of strap-down INS and GPS based on adaptive error damping*, Robotics and Autonomous Systems, 2010, Vol.58, No.10, pp.1117-1129.

[17] SALYCHEV,O.S.: *Applied Inertial Navigation: Problems and Solutions*, BMSTU Press, Moscow, Russia, 2004.

Received: 29.04.2014.

Adaptivno prigušenje grešaka u INS/GPS/baro-altimetar integrisanom navigacijskom sistemu

U inercijalnim navigacijskim sistemima (INS) greška visine divergira eksponencijalno, a naročito kod senzora niske klase tačnosti. Radi otklanjanja divergencije greške visine, upotrebljeni su sistem globalnog pozicioniranja (GPS) i barometarski visinomer (baro-visinomer). U ovom radu je opisano prigušenje grešaka vertikalnog kanala integrisanog navigacijskog sistema INS/GPS i baro-visinomera pomoću petlje trećeg reda za stabilizaciju vertikalnog kanala i uz primenu adaptivnih koeficijenata za prigušenje grešaka. Integracija je urađena pomoću proširenog Kalmanovog filtra (PKF) sa kontrolnim signalom. Karakteristike predloženog modela su analizirane pomoću simulacije i eksperimentalno, pomoću vozila. Rezultati izvedene analize pokazuju da navigacijsko rešenje INS/GPS /baro-visinomer navigacijskog sistema može da poboljša tačnost primenom adaptivnih kontrolnih koeficijenata greške u kontrolnom signalu PKF.

Ključne reči: **inercijalna navigacija, navigacioni sistem, globalni pozicioni sistem, barometarski visinomer, kalmanov filtar, korekcija greške, algoritam.**

Адаптивные демпфирования ошибок в INS / GPS / баро-высотомера интегрированой системы навигации

В инерциальных навигационных системах (ИНС) ошибка высоты экспоненциально расходится, а особенно при низкой классе точности датчика. В целях устранения ошибки расхождения в высоте, были использованы системы глобального позиционирования (GPS) и барометрического высотомера (баро-высотомер). В этой статье описаны затухания ошибок позиционирования вертикального канала интегрированной навигационной системы INS / GPS и баро-высотомера с помощью цикла третьего порядка для стабилизации вертикального канала и с использованием адаптивных коэффициентов для демпфирования ошибок.Интегрирование производится с помощью расширенного фильтра Калмана (РФК) с управляющим сигналом. Особенности предлагаемой модели анализируются с помощью моделирования и экспериментально, с использованием транспортных средств. Результаты проведённого анализа показывают, что навигационное решение INS / GPS / баро-высотомер навигационной системы может повысить точность с помощью адаптивных контрольных коэффициентов ошибки в сигнале управления РФК.

Ключевые слова: **инерциальная навигация, навигационная система, глобальная система позиционирования, барометрический высотомер, фильтр Калмана, коррекции ошибок, алгоритм.**

Etouffement adaptif des erreurs dans le système de baromètre d'altitude de navigation SNI / GPS intégré

Dans les systèmes de navigation inertielle (SNI) l'erreur d'altitude diverge exponentiellement surtout chez les capteurs de précision de basse classe. Pour supprimer la divergence de l'erreur d'altitude on a utilisé le système global de positionnement (GPS) et le baromètre d'altitude (altimètre barométrique). Dans ce travail on a décrit l'étouffement des erreurs du canal vertical chez le système de navigation SNI/GPS intégré et le baromètre d'altitude au moyen de la boucle de la troisième ordre pour la stabilisation du canal vertical et en appliquant les coefficients adaptifs pour l'étouffement des erreurs. L'intégration a été faite à l'aide du filtre Kalman élargi avec le signal de contrôle. Les caractéristiques du modèle proposé ont été analysées par la simulation et expérimentalement en utilisant les véhicules. Les résultats de cette analyse démontrent que la solution de navigation SNI / GPS / baromètre d'altitude du système de navigation peut améliorer la précision par l'emploi des coefficients adaptifs de contrôle de l'erreur dans le signal de contrôle du filtre Kalman.

Mots clés: **navigation inertielle, système de navigation, système global de position, baromètre d'altitude, filtre Kalman, correction d'erreur, algorithme.**