REAL-TIME IMPLEMENTATION OF A LOW COST INS/GPS KALMAN FILTER BASED NAVIGATION SYSTEM

Elder M. Hemerly
Technological Institute of Aeronautics - Electronics Division, Systems and Control Department
Pça. Mal. Eduardo Gomes, 50 - Vila das Acácias 12228-900 São José dos Campos/ SP - Brazil
hemerly@ita.br

Valter R. Schad
NAVCON- Navegação e Controle Ind. & Com. Ltda.
Rua Marabá, 35 – Parque Industrial 12235-780 São José dos Campos /SP - Brazil
valterschad@navcon.com.br

Abstract. *The design of an INS/GPS navigation system, based on the integration of a low cost inertial measurement unit (IMU) with GPS, by means of a Kalman Filter, was presented recently by the authors. For getting the best performance from this fusion, the tight integration scheme (which employs raw GPS readings) was used with the feedback configuration. In that work the navigation system performance was evaluated via simulation only. In this work preliminary experimental results are presented and discussed. For the experiments the following hardware was used: MotionPak IMU, sampled at 50 Hz, and Trimble GPS receiver, with 1 Hz readings, and the software was coded in C. Three highly desirable features of the navigation system are displayed: 1) capability for real time IMU calibration; 2) interpolation between GPS readings and 3) autonomy, in the sense that GPS signal can be lost for short periods of time. This experimental result seems to be the first of its kind in Brazil.*

Keywords*: INS, GPS, sensor fusion, Kalman filter*

1. Introduction

Inertial navigation, by using accelerometers and gyrometers readings, has two benefits inherited from these sensors: there is no signal transmition, thence no possibility of jamming or signal loss. However, there is a basic weakness in this navigation procedure: any imperfection in the sensors, such as bias, can produce unbounded velocity and position errors. Further details on inertial navigation can be found in Titterton and Weston, 1997 and Farrell and Barth, 1999, where some schemes involving auxilary sensors, such as VOR, DME, TACAN, Omega, LORAN, GPS, Doppler radar and baroaltimeter, are employed for bounding the aforementioned errors.

In this work the GPS (Global Positioning System) is used to assist the inertial navigation, due to its following good characteristics: global coverage, fast acquisition, good accuracy and receivers low cost. For general details on the GPS principles, see Farrell and Barth, 1999. Experimental results for the INS/GPS fusion, by means of the Kalman filter, can be found in Ohlmeyer, 1999; Faruqi, 2000; Salychev, 2000 and Walchko, 2003, but all the relevant details for the proper filter tuning are omitted, due to the potential commercial value.

The brazilian literature indicates that the INS and GPS sensors are usually treated and employed separately. For instance, the impact of accelerometer parameters accuracy in the navigation error is investigated in Waldmann and Cerávolo, 2000, and in Junqueira and Barros, 2003 the design and modeling of a dynamically tuned gyroscope is presented. Regarding the GPS, there are some works using Kalman filter, but only for static applications, such as Gomes, Kuga and Lopes, 2003. One of the few works reporting the INS/GPS is Schad, Pires and Durão, 2001, but this paper only concerns the general aspects involved in the loose integration, and no simulation result is presented.

The only work in Brazil dealing with the INS/GPS tight dynamic fusion seems to be Hemerly and Schad, 2004, where a Kalman filter was employed to implement a 17 state estimator, including 3 kinds of error estimates: trajectory related (position, velocity and attitude), IMU related (accelerometer and gyrometer bias) and GPS related (clock bias and drift). Although representing a considerable progress, that work presents only simulated results.

In the present work the procedure for INS/GPS described in Hemerly and Schad, 2004 is tested with real data. The hardware employed for data acquisition was comprised by the MotionPak IMU, sampled at 50 Hz, and Trimble GPS receiver sampled at 1 Hz. All the details regarding data synchronization, IMU sampling and GPS raw data reading was performed by NAVCON. This experiment should be understood as a preliminary step toward performance evaluation, for the following reasons: a) the use of DGPS was advisable instead of GPS, in order to provide a smoother trajectory, but was not available in this experiment, and b) it would be useful to have a ground truth for performance comparison, provided for instance by a highly accurate commercial positioning system. It is expected that NAVCON will soon have such a system, which will then enable more detailed performance evaluation.

This paper is organized as follows: in section 2 the dynamic equation for the error propagation is established, which is used by the Kalman filter. Some details about the Kalman filter for implementing the INS/GPS fusion via the tight approach are also presented in section 2. The experiment is described in secion 3, which also includes a discussion of the main results obtained. The conclusions are then presented in section 4.

2. Error Model and the Kalman Filter for Tight Fusion

The basic equations for the error model and the Kalman filter is presented in what follows, and is a summary of Hemerly and Schad, 2004. For further details, see Walchko, 2003; Salychev, 2000; Farrell and Barth, 1999 and Ohlmeyer, 1999.

As already mentioned, the filter state here incorporates 9 variables associated with the body trajectory (position, velocity and attitude), 6 regarding the IMU (gyrometer drift and accelerometer bias) and 2 associated with the GPS (clock bias and drift). Therefore, 17 variables must be estimated and the associated state is defined by

$$x = \begin{bmatrix} \delta r \\ \delta v \\ \delta\phi \\ \delta w \\ \delta f \\ \delta b \\ \delta d \end{bmatrix} = \begin{bmatrix} \textit{Position Error in ECEF coordinates} \\ \textit{Velocity Error in ECEF coordinates} \\ \textit{Attitude Error} \\ \textit{Gyrometer drift error} \\ \textit{Accelerometer bias error} \\ \textit{GPS receiver clock bias error} \\ \textit{GPS receiver clock drift error} \end{bmatrix} \tag{1}$$

where $\delta r, \delta v, \delta\phi, \delta w, \delta f$ are vector in $\Re^3$, and δb and δd are scalars.

In order to apply the Kalman filter to estimate the state defined in (1), two associated equation are required: the dynamic equation involving (1) and the corresponding output equation. As in Hemerly and Schad, 2004, these equations are

$$\begin{aligned} &\dot{x}(t) = A(t)x(t) \ \ \textit{(continuous time)} \\ &y(k) = Cx(k) \ \ \ \textit{(discrete time)} \end{aligned} \tag{2}$$

where $A(t) \in \Re^{17x17}$ is given by

$$A(t) = \begin{bmatrix} 0_{3x3} & I_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} & 0 & 0 \\ G + \Delta G - \tilde{\Omega}(t).\tilde{\Omega}(t) & -2\tilde{\Omega}(t) & \tilde{a}(t) & 0_{3x3} & C_b^e(t) & 0 & 0 \\ 0_{3x3} & 0_{3x3} & -\tilde{\Omega}(t) & -C_b^e(t) & 0_{3x3} & 0 & 0 \\ 0_{3x3} & 0_{3x3} & 0_{3x3} & -\beta_w.I_{3x3} & 0_{3x3} & 0 & 0 \\ 0_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} & -\beta_a.I_{3x3} & 0 & 0 \\ 0_{1x3} & 0_{1x3} & 0_{1x3} & 0_{1x3} & 0_{1x3} & 0 & 1 \\ 0_{1x3} & 0_{1x3} & 0_{1x3} & 0_{1x3} & 0_{1x3} & 0 & -\beta_d \end{bmatrix} \tag{3}$$

and the ouput matrix $C(t) \in \Re^{2nx17}$ is

$$C = \begin{bmatrix} -u_1^T(t_2) & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 1 & 0 \\ -u_2^T(t_2) & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -u_n^T(t_2) & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & \mathbf{0}^T & 1 & 0 \\ -\left(u_1^T(t_2) - u_1^T(t_1)\right)^T & -\Delta t.u_1^T(t_1) & \frac{1}{2}(\Delta t)^2.u_1^T(t_1).\tilde{a}(t_2) & \mathbf{0}^T & \frac{1}{2}(\Delta t)^2.u_1^T(t_1).C_b^e(t_2) & 0 & \Delta t \\ -\left(u_2^T(t_2) - u_2^T(t_1)\right)^T & -\Delta t.u_2^T(t_1) & \frac{1}{2}(\Delta t)^2.u_2^T(t_1).\tilde{a}(t_2) & \mathbf{0}^T & \frac{1}{2}(\Delta t)^2.u_2^T(t_1).C_b^e(t_2) & 0 & \Delta t \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -\left(u_n^T(t_2) - u_n^T(t_1)\right)^T & -\Delta t.u_n^T(t_1) & \frac{1}{2}(\Delta t)^2.u_n^T(t_1).\tilde{a}(t_2) & \mathbf{0}^T & \frac{1}{2}(\Delta t)^2.u_n^T(t_1).C_b^e(t_2) & 0 & \Delta t \end{bmatrix} \tag{4}$$

where I_{3x3} is the *3x3* identity matrix; 0_{3x3}: null *3x3* matrix; β: correlation time inverse; *n*: *n-th* GPS satellite; t_2: present time; t_1: previous time; $\Delta t = t_2 - t_1$; *u*: unity vector from the receiver to the satellite; *G*: gravity and ΔG: gravity derivative.

By supposing that *n* satellites are visible at time *t*, the output equation (2) is given by

$$y = \begin{bmatrix} \rho_{IN} - \rho_1 \\ \rho_{IN} - \rho_2 \\ \vdots \\ \rho_{IN} - \rho_n \\ \Delta\rho_{IN} - \Delta\rho_1 \\ \Delta\rho_{IN} - \Delta\rho_2 \\ \vdots \\ \Delta\rho_{IN} - \Delta\rho_n \end{bmatrix} \in \Re^{2n} \qquad (5)$$

where ρ_{IN} : pseudodistance calculated by using the inertial measurements; $\Delta\rho_{IN}$: deltadistance calculated by using the inertial measurements, and ρ_n : pseudodistance provided by the receiver for the *n-th* visible satellite.

The basic flowchart for estimating the state (1) via Kalman filter, given (2), (3) and the stochastic characterizations for the IMU and GPS sensors, is shown in Fig. 1.

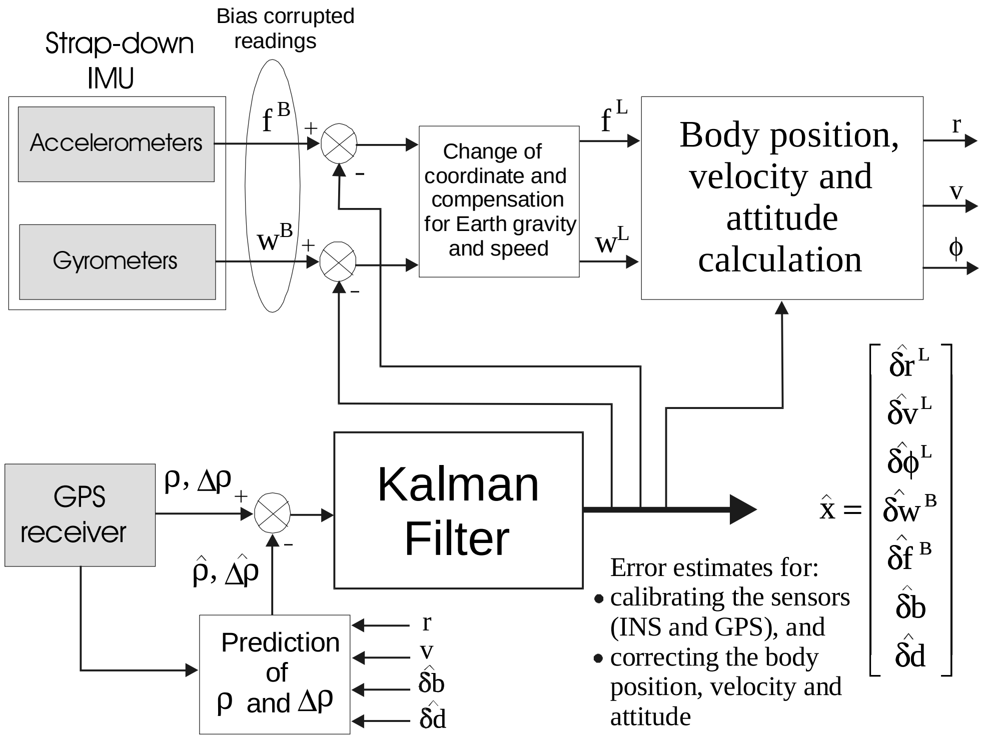

Figure 1. Basic flowchart for INS/GPS integration via Kalman filter.

As already suggested in Fig. 1, the Kalman filter is estimating 3 classes of variables, which are completely different in scope, but which have impact upon the navigator accuracy: the 3 first variables (position, velocity and attitude error) are used to correct the final body trajectory and orientation; the 2 which follows (gyrometer drift and accelerometer bias) are used to calibrate the inertial sensor, and the last 2 (GPS receiver clock bias and drift) are used to calibrate the GPS receiver. Particularly relevant for the purposes of the paper is the inertial sensor calibration, since low cost IMU (and then low quality) is used. Therefore, without this real time calibration, the navigator capability for providing accurate trajectory would be hampered when the GPS signal is temporarily lost.

For this experiment, the flowchart in Fig. 1 was coded in ANSI C. For numerical robustness, the Bierman UD factorization was employed in the Kalman filter implementation, see Grewal and Andrews, 1993.

3. Experimental Results

The hardware was mounted in a vehicle and driven around a road close to NAVCON, whose longitude *x* latitude in degrees is shown in Fig. 2, and was basically planar.

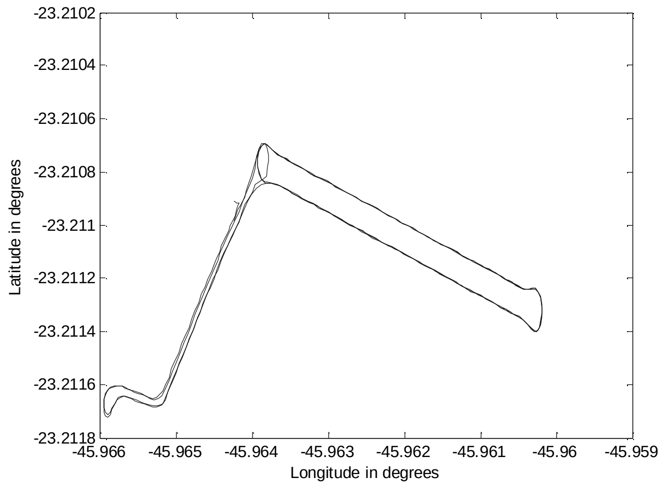

Figure 2. Route taken in this experiment.

The accelerometer and gyrometer readings corresponding to the route shown in Fig. 2 where quite noisy, thence they were filtered by a third order Chebyschev digital filter. These filtered values are shown in Fig. 3.

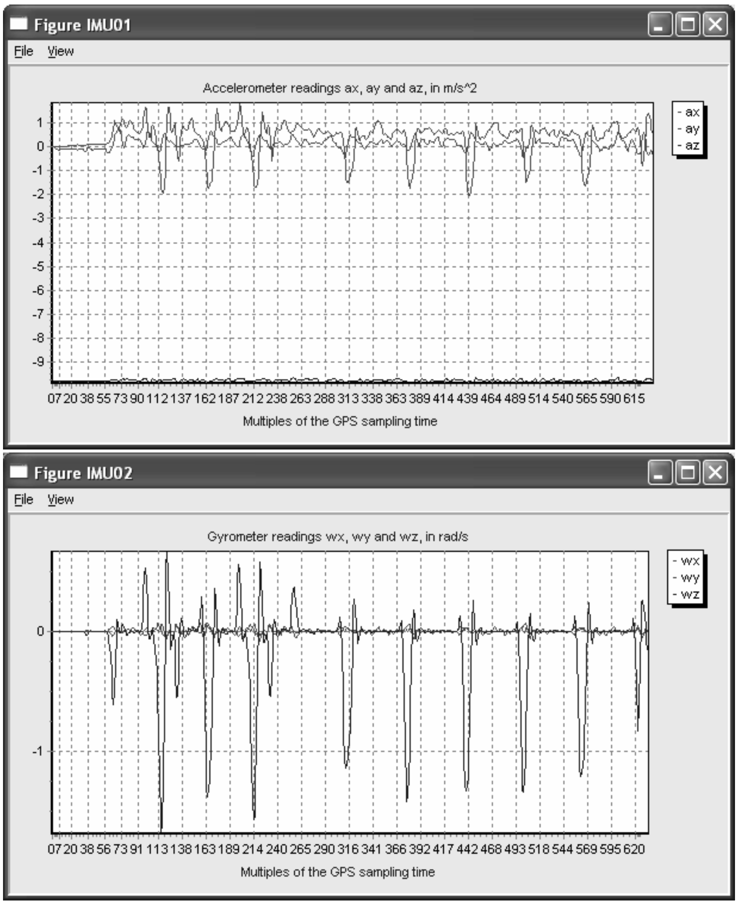

Figure 3. Accelerometer and gyrometer readings, in m / s^2 and rad / s, respectively, corresponding to the route shown in Fig. 2. GPS sampling time is 1s.

The Kalman filter was tuned and applied to the experimental data. Due to space limitation, only some variables in Fig. 1 will be displayed. The body position, which corresponds to the output variable *r* in Fig. 2, is shown in Fig. 4.

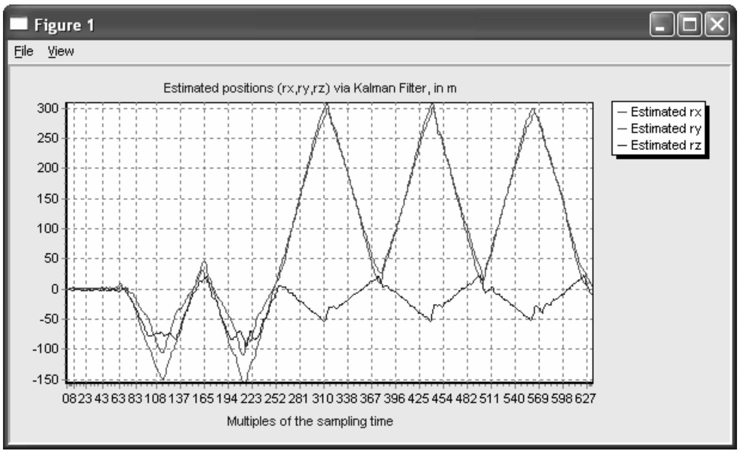

Figure 4. Body position in ECEF coordinate.

Since there is no ground truth to which to compare the result in Fig. 4, since at the time of the experiment no accurate position system was available, the position estimates in Fig. 4 were then compared to the navigation solution given by the GPS, which is accurate only for very low body dynamics. The errors were small, with the magnitude of the GPS accuracy.

A better index of performance in this case concerns the IMU calibration provided by the Kalman filter. The behavior of the gyrometer bias estimate in yaw is shown in Fig. 5.

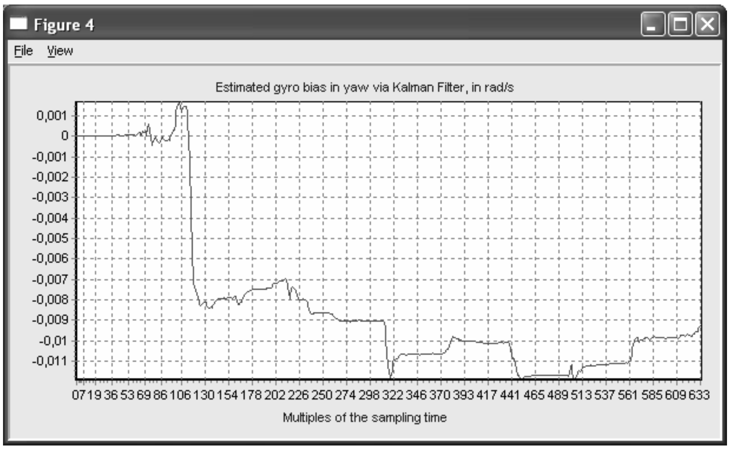

Figure 5. Gyrometer bias estimate for yaw, in rad/s.

Since the true yaw bias was unknown, its estimate was started as 0 in Fig. 5. This estimate improves as time goes on, and seems to converge to a value around -0.01 rad/s, value which is compatible with the low price IMU used.

One of the main reasons motivating the INS/GPS fusion as described in this paper is to design a navigator which can stand temporary loss of the GPS signal. We then consider the case in which the GPS signal is lost at the beginning of the counterclockwise turn in the right of Fig. 2, which is an unfavorable scenario: if the user had only GPS to navigate and employed the heuristics of interpolating the position based on the previous values, then the turn would simply be entirely missed. However, when the INS/GPS fusion is used, the following behavior is expected: when the GPS signal is lost, the navigator keeps calculating the body trajectory and attitude using solely the inertial readings. Therefore, if the inertial sensors are well calibrated, then the navigation accuracy will not be considerably spoiled till the GPS signal is restored. This behavior is shown in Fig. 6, where the GPS signal is lost at point A and restored at point B, 10 seconds later. Between these two points, the inertial sensor readings were the only information used by the navigator and the turn was correctly detected and followed with increasing error, till the GPS signal is restored and the error is once again bounded by the Kalman filter.

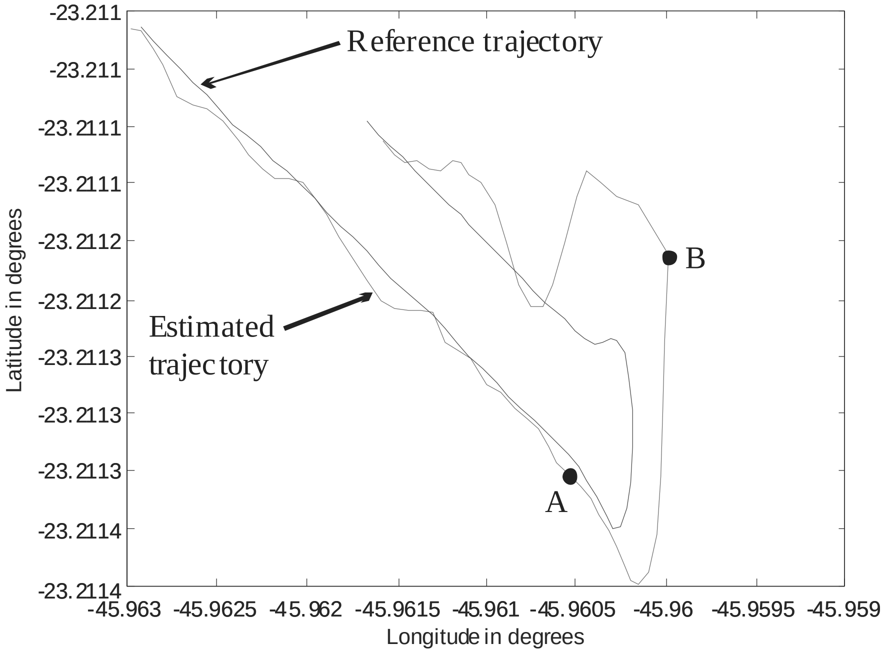

Figure 6. Experiment showing the effect of temporary loss of GPS signal: at point A the signal is lost and is restored 10 seconds later at point B.

A further remark about the estimated trajectory in Fig. 6 is in order: its bouncing behavior prior to the GPS signal loss is due to the fact this experiment is employing GPS readings, whose precision is not too good. The use of DGPS is however intended in order to smooth the estimated trajectory and will be the follow-up of this work.

4. Conclusions

Experimental results obtained for low cost INS/GPS Kalman filter based navigation system were reported, which exhibits the required capabilities: real time IMU calibration, interpolation between GPS readings and autonomy, in the sense that GPS signal can be lost for short periods of time. These results seem to be one of the first to be carried out in Brazil, and should be regarded as preliminary for 2 main reasons: a) no ground truth was available for a complete performance evaluation, and b) DGPS was not available, and as a consequence the trajectory was not as smooth as expected. Both deficiencies will be removed soon, thereby enabling better results.

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References

Farrell, J.A., Barth, M. (1999). *The Global Positioning System and Inertial Navigation*. McGraw-Hill, New York.

Faruqui, F.A. (2000). Non-Linear Mathematical Model for Integrated Global Positioning/Inertial Navigation Systems. *Applied Math. And Comput*., 15, pp. 191-212.

Gomes, V.M., Kuga, H.H., Lopes, R.V.F. (2003). Filtering GPS Navigation Solutions for Static Positioning. *17h International Congress of Mechanical Engineering*, São Paulo, COBEM2003-0516.

Grewal, M.S., Andrews, A.P. (1993). *Kalman Filtering – Theory and Practice*. Prentice Hall, New Jersey.

Hemerly,E.M. e Schad,V.R. (2004). Sistema de Navegação de Baixo Custo baseado na Fusão INS/GPS usando Filtro de Kalman. Anais do CBA2004, Gramado-RS, 2004.

Junqueira, F.C., Barros, E. A. (2003). Development of a Dynamically Tuned Gyroscope-DTG. *17h International Congress of Mechanical Engineering*, São Paulo, COBEM2003-1296.

Ohlmeyer, E.J., Pepitone, T.R., Miller, B.L. (1999). Assessment of Integrated GPS/INS for the EX-171 Extended Range Guided Munition. *Naval Surface Warfare Center-TR*, USA.

Schad, V.R., Pires, C.L.G, Durão, O.C. (2001). Sistema Modular de Atitude e Navegação. *Anais do III SBEIN– Simpósio Brasileiro de Engenharia Inercial*. Rio de Janeiro-RJ.

Salychev, O.S., Voronov, V.V. (2000). Low Cost INS/GPS Integration: Concept and Testing. *Institute of Navigation Technical Meeting*/Anaheim, CA.

Titterton, D.H., Weston, J.L (1997). *Strapdown Inertial Navigation Technology*. Peter Peregrinus Ltd., London.

Walcho, K.J., Nechyba, M.C., Schwartz, E. , Arroyo, A. (2003). Embedded Low Cost Inertial Navigation System. *Florida Conference on Recents Advances in Robotics*, FAU, Dania Beach-FL.

Waldmann, J. e Cerávolo, C.E.P. (2000). SIMNAVIN: Avaliação do Impacto da Qualidade de Sensores Inerciais Montados em Plataforma Solidária sobre os Erros de Navegação. *Anais do XII CBA*, Florianópolis-SC, pp. 1808-1813.

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