VEHICLE DYNAMICS AIDING TECHNIQUE FOR USBL/INS UNDERWATER NAVIGATION SYSTEM

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Abstract: This paper presents a Vehicle Dynamics (VD) aiding technique to enhance position, velocity, and attitude error estimation in low-cost Inertial Navigation Systems (INS), with application to Underwater Vehicles (UV). The VD model is directly embedded in an Extended Kalman Filter (EKF) and provides specific information about the rigid body tridimensional motion unavailable from the INS computations, thus allowing for a comprehensive improvement of the overall navigation system performance. A tightly-coupled inverted USBL is also adopted to enhance position and attitude estimation using range measurements to transponders in the vehicle's mission area. The overall Navigation System accuracy improvement is assessed in simulation using a nonlinear model of the Infante UV.

Keywords: Inertial navigation, Sensor fusion, Vehicle dynamics

1. INTRODUCTION

Recent technological developments and environmental research have boosted the use of Underwater Vehicles (UV) to ensure the fulfillment of several tasks at sea. The missions to be carried out include environmental monitoring, geological and biological surveys, and inspections of several underwater structures such as harbors and pipelines (Pascoal *et al.*, 2000). The execution of these tasks often requires high accuracy instrument positioning at affordable costs, and consequently the use of compact, low-cost, high performance, robust positioning and navigation systems that can accurately estimate the UV position and orientation.

Performance degradation and limitations inherent to low-cost Inertial Navigation Systems (INS), associated to open-loop unbounded estimation errors, uncompensated sensor noise, and bias effects, are often tackled by merging additional information sources using nonlinear filtering techniques. Among a diverse set of techniques, the Extended Kalman Filter (EKF) in a direct-feedback configuration (Brown and Hwang, 1997) is commonly adopted to estimate and compensate the INS integration errors buildup.

Previous work by the authors has focused on solving the sensor fusion problem using an Ultra-Short Baseline (USBL) array of receivers to compute the

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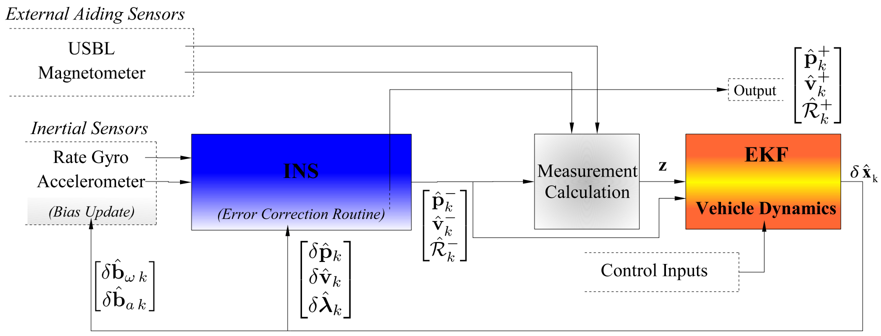

Fig. 2. Navigation system block diagram

position of one or more transponders placed at known positions in the UV mission area. A tightly-coupled solution was presented in (Morgado *et al.*, 2006) in which the set of range measurements (from the transponders to each receiver) available at the USBL array is directly embedded in the EKF instead of using the transponders position estimates as measurements (loosely-coupled solution).

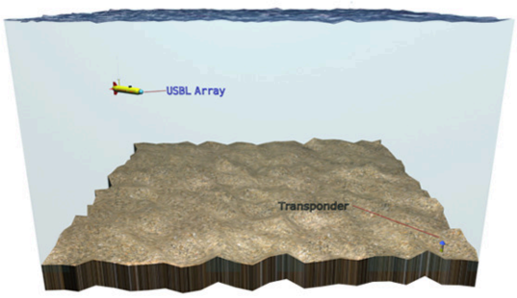

Fig. 1. Mission scenario

The scientific community striving to improve low-cost navigation systems accuracy has directed much of the efforts towards the inclusion of Vehicle Dynamics (VD) model in the INS (Bryson and Sukkarieh, 2004; Koifman and Bar-Itzhack, 1999; Julier and Durrant-Whyte, 2003). The vehicle model dynamics yield unique data that provides a comprehensive set of observations of the inertial system errors and allows for enhanced INS error compensation. Moreover, the vehicle model is a software based, passive information source valid for most operating scenarios, that is not subject to interference and jamming as generic aiding sensors are.

In this paper we present a VD model inclusion technique for underwater vehicles inspired on the embedding methodology recently proposed in (Vasconcelos *et al.*, 2006). Simulation results are presented using a VD model of the Infante UV developed at ISR (Silvestre and Pascoal, 2004). The considered mission scenario is illustrated in Figure 1, where the vehicle is equipped with an INS and an USBL array, in an inverted USBL configuration (Vickery, 1998), that interrogates transponders located in known positions of the vehicle's mission area.

The paper is organized as follows: the main aspects of the navigation system and the proposed architecture are reviewed in Section 2. Section 3 describes the USBL system and the integration of the sensors information into the navigation system structure. The VD model integration technique is brought to full detail in Section 4, to improve UV navigation systems accuracy. Simulation results of the overall navigation system are presented in Section 5. Finally, Section 6 draws some concluding remarks and comments on future work.

2. NAVIGATION SYSTEM ARCHITECTURE

The proposed navigation architecture is depicted in Figure 2. The INS is the backbone algorithm (Savage, 1998*a*; Savage, 1998*b*) that performs attitude, velocity and position numerical integration from rate gyro and accelerometer triads data, rigidly mounted on the vehicle structure (strapdown configuration). The non-ideal inertial sensor effects due to noise and bias are dynamically compensated by the EKF that estimates position, velocity, attitude and bias compensation errors, according to the direct-feedback configuration shown in the figure. Given the control inputs, the VD equations are implemented in the EKF state model and merged with the INS data, which allows for a significant improvement of the INS error estimates accuracy.

The INS multi-rate approach, based on the work detailed in (Savage, 1998*a*; Savage, 1998*b*), computes the dynamic angular rate/acceleration effects using high-speed, low order algorithms, whose output is periodically fed to a moderate-speed algorithm that computes attitude/velocity resorting to exact, closed-form equations. The numerical integration performed by the INS algorithms takes into account the angular and linear velocity and position high-frequency motions, referred to as coning, sculling, and scrolling respectively, to avoid estimation errors buildup.

The inputs provided to the inertial algorithms are the accelerometer and rate gyro readings, corrupted by zero mean white noise $\mathbf{n}$ and random walk bias, $\dot{\bar{\mathbf{b}}} = \mathbf{n}_b$, yielding

$$ {}^B\mathbf{a}_{SF} = {}^B\bar{\mathbf{a}} + {}^B\bar{\mathbf{g}} - \delta\mathbf{b}_a + \mathbf{n}_a, \quad \boldsymbol{\omega} = \bar{\boldsymbol{\omega}} - \delta\mathbf{b}_\omega + \mathbf{n}_\omega $$

where $\delta\mathbf{b} = \mathbf{b} - \bar{\mathbf{b}}$ denotes bias compensation error, $\bar{\mathbf{b}}$ is the nominal bias, $\mathbf{b}$ is the compensated bias, ${}^B\bar{\mathbf{g}}$ is the nominal gravity vector, and the subscripts a and ω identify accelerometer and rate gyro quantities, respectively.

The moderate-speed inertial algorithms attitude output is represented in Direction Cosine Matrix (DCM) form, and velocity and position are expressed in Earth frame coordinates, $\mathbf{v}$ and $\mathbf{p}$ respectively. For further details on the INS algorithm adopted in this work, see (Morgado *et al.*, 2006) and references therein.

The EKF error equations, based on perturbational rigid body kinematics, were brought to full detail by Britting (Britting, 1971), and are applied to local navigation by modeling the position, velocity, attitude and bias compensation errors dynamics, respectively

$$ \begin{aligned} \delta\dot{\mathbf{p}} &= \delta\mathbf{v} \\ \delta\dot{\mathbf{v}} &= -\mathcal{R}\delta\mathbf{b}_a - [\mathcal{R}\,{}^B\mathbf{a}_{SF}\times]\delta\boldsymbol{\lambda} + \mathcal{R}\mathbf{n}_a \\ \delta\dot{\boldsymbol{\lambda}} &= -\mathcal{R}\delta\mathbf{b}_\omega + \mathcal{R}\mathbf{n}_\omega \\ \delta\dot{\mathbf{b}}_a &= -\mathbf{n}_{b_a} \\ \delta\dot{\mathbf{b}}_\omega &= -\mathbf{n}_{b_\omega} \end{aligned} $$

where the position and velocity linear errors are defined respectively by

$$ \delta\mathbf{p} = \mathbf{p} - \bar{\mathbf{p}}\ ,\ \delta\mathbf{v} = \mathbf{v} - \bar{\mathbf{v}}, \tag{1} $$

matrix $\mathcal{R}$ is the shorthand notation for Body to Earth coordinate frames rotation matrix, ${}^E_B\mathbf{R}$, $\bar{\mathbf{p}}$ is the nominal Body frame origin position relative to the Earth coordinate frame, $\bar{\mathbf{v}}$ is the nominal linear velocity, the attitude error rotation vector $\delta\boldsymbol{\lambda}$ is defined by $\mathbf{R}(\delta\boldsymbol{\lambda}) = \mathcal{R}\bar{\mathcal{R}}'$, bearing a first order approximation

$$ \mathbf{R}(\delta\boldsymbol{\lambda}) \simeq \mathbf{I}_{3\times3} + [\delta\boldsymbol{\lambda}\times] \Rightarrow [\delta\boldsymbol{\lambda}\times] \simeq \mathcal{R}\bar{\mathcal{R}}' - \mathbf{I}_{3\times3} \tag{2} $$

of the Direction Cosine Matrix (DCM), where $\bar{\mathcal{R}}$ represents nominal rotation matrix.

The EKF error estimates are fed into the INS error correction routines as depicted in Figure 2. The INS attitude estimate, $\mathcal{R}_k^-$, is compensated using the rotation error matrix $\mathbf{R}(\delta\boldsymbol{\lambda})$ definition, which yields

$$ \mathcal{R}_k^+ = \mathbf{R}_k'(\delta\hat{\boldsymbol{\lambda}}_k)\mathcal{R}_k^- $$

where $\mathbf{R}_k'(\delta\hat{\boldsymbol{\lambda}}_k)$ is parameterized by the rotation vector $\delta\hat{\boldsymbol{\lambda}}_k$ according to the DCM form. The remaining state variables are linearly compensated using

$$ \begin{aligned} \mathbf{p}_k^+ &= \mathbf{p}_k^- - \delta\hat{\mathbf{p}}_k \quad &,\quad \mathbf{v}_k^+ &= \mathbf{v}_k^- - \delta\hat{\mathbf{v}}_k \\ \mathbf{b}_{a\ k}^+ &= \mathbf{b}_{a\ k}^- - \delta\hat{\mathbf{b}}_{a\ k} \quad &,\quad \mathbf{b}_{\omega\ k}^+ &= \mathbf{b}_{\omega\ k}^- - \delta\hat{\mathbf{b}}_{\omega\ k} \end{aligned} $$

After the error correction procedure is completed, the EKF error estimates are reset maintaining the filter linearization assumptions valid.

3. USBL SYSTEM

The USBL sensor consists of a small and compact array of acoustic transducers that allows for the computation of a transponder position in the vehicle coordinate frame, based on the travel time of acoustic signals emitted by the transponder. The measurements provided by these systems have very low update rates (typically below 1 Hz) imposed by physical limitations and mission specific constraints (velocity of acoustic waves in the water, multi-path phenomena, and other disturbances), with a performance that degrades as the transponder/USBL distance increases.

The measurement of travel time is obtained from the round trip travel time of the acoustic signals between the USBL array and the transponder. Taking into account the quantization performed by the acoustic system, the travel time measurements for receiver i are given by

$$ t_i = T_s \left[\frac{\bar{t}_i + \varepsilon_c}{T_s}\right] \tag{3} $$

where $\bar{t}_i$ is the nominal travel time, ε_c represents the common mode noise for transponder j (common to all receivers - includes transponder-receiver relative motion time-scaling effects and errors in sound propagation velocity), T_s is the acoustic sampling period and $[\cdot]$ represents the mathematical *round* operator. The travel time measurements are considered to be approximately described by

$$ t_i = \bar{t}_i + \eta_i \tag{4} $$

where η_i represents the measurement noise for receiver i (corresponds to the differential quantization error induced by the acoustic system sampling frequency and the digital implementation of the detection algorithms).

The measurement of distance obtained from the round trip travel time of the acoustic signals between the USBL array and the transponders, is given by

$$ \rho_{ji} = \bar{\rho}_{ji} + v_p\eta_i = v_p\bar{t}_{ji} + v_p\eta_i \tag{5} $$

where $\bar{\rho}_{ji}$ and $\bar{t}_{ji}$ represent, respectively, the nominal distance and travel time from transponder j to receiver i, and v_p represents the propagation velocity of acoustic waves underwater.

The distance between transponder j and receiver i is given by

$$ \bar{\rho}_{ji} = \left\| {}^E\bar{\mathbf{p}}_{e_j} - {}^E\bar{\mathbf{p}}_{r_i} \right\| = \left\| {}^E\bar{\mathbf{p}}_{e_j} - \bar{\mathbf{p}} - \bar{\mathcal{R}}\,{}^B\bar{\mathbf{p}}_{r_i} \right\| \tag{6} $$

where ${}^E\bar{\mathbf{p}}_{e_j}$ and ${}^E\bar{\mathbf{p}}_{r_i}$ represent the position of transponder j and receiver i respectively in Earth coordinate frame, and ${}^B\bar{\mathbf{p}}_{r_i}$ is the position of receiver i in Body coordinate frame.

Using the position error definition (1) and the approximation (2) in (6) yields (Morgado *et al.*, 2006)

$$\bar{\rho}_{ji} \approx \left\| {}^{E}\bar{\mathbf{p}}_{e_j} - \mathbf{p} + \delta\mathbf{p} - \mathcal{R}\,{}^{B}\bar{\mathbf{p}}_{r_i} - \left[\mathcal{R}\,{}^{B}\bar{\mathbf{p}}_{r_i}\times\right]\delta\boldsymbol{\lambda} \right\| \tag{7}$$

which is integrated into the EKF as observations for each receiver by linearizing $\bar{\rho}_{ji}$ about the filter state space variables and the INS estimated quantities.

4. VEHICLE AIDING

Merging the VD model information with the INS enhances the overall navigation system observability, since the vehicle model provides redundant angular and linear velocities estimates given the control inputs to the vehicles actuators (thrusters, control surfaces deflection angles, etc). The VD aiding architecture adopted in this paper is inspired on the work presented in (Vasconcelos *et al.*, 2006). As depicted in Figure 2, the vehicle model dynamic equations are directly integrated in the filter state space and are used to propagate the INS quantities, allowing the EKF to estimate and compensate for the inertial errors.

Consider the VD equations for a generic UV

$$\dot{\bar{\boldsymbol{\omega}}} = f_\omega\left(\bar{\boldsymbol{\omega}}, \bar{\mathbf{u}}, \bar{\mathcal{R}}, \bar{\mathbf{s}}\right) \tag{8}$$

$$\dot{\bar{\mathbf{u}}} = f_u\left(\bar{\boldsymbol{\omega}}, \bar{\mathbf{u}}, \bar{\mathcal{R}}, \bar{\mathbf{s}}\right) \tag{9}$$

where $\bar{\boldsymbol{\omega}}$ is the vehicle nominal angular velocity, $\bar{\mathbf{u}}$ is the nominal linear velocity, $\bar{\mathcal{R}}$ represents the vehicle orientation relatively to the Earth coordinate frame (rotation matrix from Body to Earth coordinate frame expressed in DCM format), $\bar{\mathbf{s}}$ represents the control input vector, and the functions f_ω, f_u describe the vehicle dynamics.

The VD equations are linearized about the INS states using the first order terms of the Taylor expansion series of (8-9), and integrated in the filter state space model. Approximation of the VD equations by the first order terms of the Taylor series expansion yields

$$\dot{\bar{\boldsymbol{\omega}}} = f_\omega\left(\bar{\boldsymbol{\omega}}, \bar{\mathbf{u}}, \bar{\mathcal{R}}, \bar{\mathbf{s}}\right) \tag{10}$$

$$\approx f_\omega\left(\boldsymbol{\omega}, \mathbf{u}, \mathcal{R}, \mathbf{s}\right) - \left.\frac{\partial f_\omega}{\partial \boldsymbol{\omega}}\right|_x \delta\boldsymbol{\omega} - \left.\frac{\partial f_\omega}{\partial \mathbf{u}}\right|_x \delta\mathbf{u} - \left.\frac{\partial f_\omega}{\partial \delta\boldsymbol{\lambda}}\right|_x \delta\boldsymbol{\lambda} - \left.\frac{\partial f_\omega}{\partial \delta\mathbf{s}}\right|_x \delta\mathbf{s} \tag{11}$$

$$\dot{\bar{\mathbf{u}}} = f_u\left(\bar{\boldsymbol{\omega}}, \bar{\mathbf{u}}, \bar{\mathcal{R}}, \bar{\mathbf{s}}\right) \tag{12}$$

$$\approx f_u\left(\boldsymbol{\omega}, \mathbf{u}, \mathcal{R}, \mathbf{s}\right) - \left.\frac{\partial f_u}{\partial \boldsymbol{\omega}}\right|_x \delta\boldsymbol{\omega} - \left.\frac{\partial f_u}{\partial \mathbf{u}}\right|_x \delta\mathbf{u} - \left.\frac{\partial f_u}{\partial \delta\boldsymbol{\lambda}}\right|_x \delta\boldsymbol{\lambda} - \left.\frac{\partial f_u}{\partial \delta\mathbf{s}}\right|_x \delta\mathbf{s} \tag{13}$$

where $\delta\boldsymbol{\omega} = \boldsymbol{\omega} - \bar{\boldsymbol{\omega}}$ is the angular velocity error, $\delta\mathbf{u} = \mathbf{u} - \bar{\mathbf{u}}$ is the linear velocity error, $\delta\boldsymbol{\lambda}$ is the attitude error, $\delta\mathbf{s}$ is the control input error which is considered to be $\delta\mathbf{s} = 0_{3\times 1}$ since the control input $\mathbf{s}$ is known, and $x = (\boldsymbol{\omega}, \mathbf{v}, \mathcal{R})$ denotes the INS state estimates. The body linear velocity error $\delta\mathbf{u}$ is then expressed in terms of the INS state errors as

$$\delta\mathbf{u} = \mathcal{R}'\mathbf{v} - \bar{\mathcal{R}}'\bar{\mathbf{v}} \approx \mathcal{R}'\delta\mathbf{v} + \mathcal{R}'\left[\mathbf{v}\times\right]\delta\boldsymbol{\lambda} \tag{14}$$

and is plugged in (11) and (13) along with the angular velocity error definition $\delta\boldsymbol{\omega} = -\delta\mathbf{b}_\omega + \mathbf{n}_\omega$ bearing

$$\dot{\bar{\boldsymbol{\omega}}} \approx f_\omega\left(\boldsymbol{\omega}, \mathbf{u}, \mathcal{R}, \mathbf{s}\right) - \left.\frac{\partial f_\omega}{\partial \boldsymbol{\omega}}\right|_x \mathcal{R}'\delta\mathbf{v} - \left(\left.\frac{\partial f_\omega}{\partial \mathbf{u}}\right|_x \mathcal{R}'\left[\mathbf{v}\times\right] - \left.\frac{\partial f_\omega}{\partial \delta\boldsymbol{\lambda}}\right|_x\right)\delta\boldsymbol{\lambda} + \left.\frac{\partial f_\omega}{\partial \boldsymbol{\omega}}\right|_x \delta\mathbf{b}_\omega - \left.\frac{\partial f_\omega}{\partial \boldsymbol{\omega}}\right|_x \mathbf{n}_\omega \tag{15}$$

$$\dot{\bar{\mathbf{u}}} \approx f_u\left(\boldsymbol{\omega}, \mathbf{u}, \mathcal{R}, \mathbf{s}\right) - \left.\frac{\partial f_u}{\partial \boldsymbol{\omega}}\right|_x \mathcal{R}'\delta\mathbf{v} - \left(\left.\frac{\partial f_u}{\partial \mathbf{u}}\right|_x \mathcal{R}'\left[\mathbf{v}\times\right] - \left.\frac{\partial f_u}{\partial \delta\boldsymbol{\lambda}}\right|_x\right)\delta\boldsymbol{\lambda} + \left.\frac{\partial f_u}{\partial \boldsymbol{\omega}}\right|_x \delta\mathbf{b}_\omega - \left.\frac{\partial f_u}{\partial \boldsymbol{\omega}}\right|_x \mathbf{n}_\omega \tag{16}$$

Equations (15-16) bear a first order approximation of the VD equations as a function of the INS estimates. Equations (8-9) are numerically integrated using the inertial quantities as an initial condition, and described in the state space model of the EKF using (15-16). The filter observations are obtained from the INS estimates

$$z_\omega = \boldsymbol{\omega} = \bar{\boldsymbol{\omega}} - \delta\mathbf{b}_\omega + \mathbf{n}_\omega \tag{17}$$

$$z_u = \mathcal{R}'\mathbf{v} \tag{18}$$

$$\approx \bar{\mathcal{R}}'\left(\mathbf{I} - \left[\delta\boldsymbol{\lambda}\times\right]\right)\bar{\mathbf{v}} + \mathcal{R}'\delta\mathbf{v} \approx \bar{\mathbf{u}} + \mathcal{R}'\delta\mathbf{v} + \mathcal{R}'\left[\mathbf{v}\times\right]\delta\boldsymbol{\lambda} \tag{19}$$

which are compared to the angular and linear velocities obtained from the integration of (8-9).

The filter update equations are reformulated to account for the correlation between process and observations noises introduced by the observation of the INS estimated angular velocity in (17) (Gelb, 1974). In the prediction step, the EKF and the INS propagate the inertial states using the VD and INS equations, respectively. In the update step, the filter computes the inertial errors estimates, which are used to correct the INS and inertial sensors according to the direct-feedback structure.

5. SIMULATION RESULTS

The VD integration scheme proposed in this paper was assessed in simulation using a nonlinear model of the Infante UV developed at ISR, illustrated in Figure 3. For details on the Infante vehicle dynamic model the reader is referred to (Silvestre and Pascoal, 2004).

The USBL array is composed of five acoustic receivers, installed on the nose cone of the vehicle according to the configuration depicted in Figure 3 and detailed in Figure 4, and interrogates one transponder located at the origin of the Earth coordinate frame. The maximum distance between the receivers is 20 cm, and there are no more than three coplanar hydrophones. The Time-Of-Arrival (TOA) of the acoustic waves arriving at the receivers are considered to be disturbed by zero mean Additive White Gaussian Noise (AWGN) with a variance of $(100\mu s)^2$ prior to the quantization procedure (note that this AWGN is the same for all receivers and that the differential disturbance is induced by the quantization). The TOA at the receivers are generated in simulation using (3) whereas the respective observations are modeled in the EKF using (4). The quantization was performed with a sampling frequency of 400 kHz.

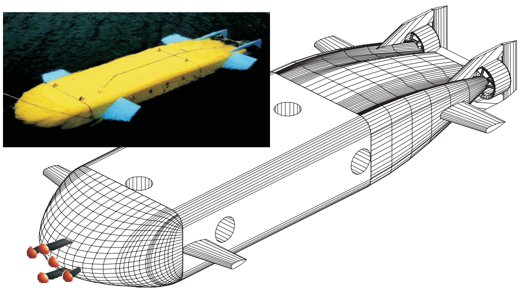

Fig. 3. Infante underwater vehicle

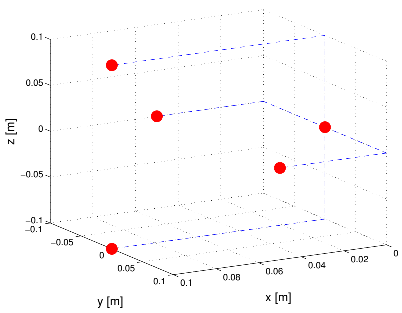

Fig. 4. Receivers installation geometry

The INS high-speed algorithm is set to run at 100 Hz and the normal-speed algorithm is synchronized with the EKF, both executed at 50 Hz. The USBL array provides measurements at 1 Hz, and the VD corrections are performed at each execution of the EKF. The white Gaussian noise and bias characteristics of the sensors are presented in Table 1. A magnetometer is also used in the proposed solution, as presented in (Morgado *et al.*, 2006), to provide measurements of the Earth Magnetic Field and yielding attitude observability improvements. In the simulations performed in this section, the bias calibration error is of one third of the nominal bias value on all inertial sensors axes.

The vehicle follows a path composed of an initial straight line with a velocity of 2 m/s followed by a dive to 10 meters and a series of 90 degrees

Table 1. Sensor errors

Sensor	**Bias**	**Noise Variance**
Rate gyro	0.05 °/s	$(0.02\ °/s)^2$
Accelerometer	10 mg	$(0.6\ mg)^2$
Magnetometer	-	$(1\ \mu G)^2$

left turns while performing a dive to 100 meters, as illustrated in Figure 5. The improvement of the VD inclusion is clearly verified in this figure, where the trajectory estimated by the navigation system running with the vehicle dynamics aiding follows closely the real trajectory.

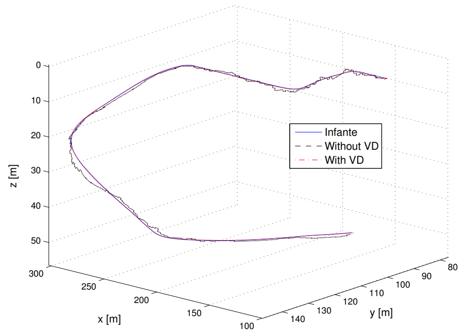

Fig. 5. Infante Vehicle trajectory

Interestingly enough, a 4th order Runge - Kutta (RK4) numerical integration method was found to be suitable for solving the discretized VD equations without loss of accuracy on the overall navigation system when compared to other higher order discrete integration schemes, and thus suitable for implementation on low power consumption DSP hardware.

The costless software based VD aiding technique contributes much to the enhancement of the vehicle linear and angular velocities estimation, as it can be evidenced by Figure 6 where the linear velocity estimation error is depicted. Indeed, this contribution is also positively reflected on improved position and attitude estimates as it can be seen from the RMS values of the position, velocity and attitude estimation errors (computed after the initial 20 seconds transient is surpassed) presented in Table 2, where $\delta\psi$, $\delta\theta$, and $\delta\phi$ represent respectively the Yaw, Pitch, and Roll angle estimation errors. Figure 7 clearly evidences the enhancement in the vehicle position estimates.

Table 2. Summary of estimation errors (RMS)

Position	δp_x [m]	δp_y [m]	δp_z [m]
Without VD	0.4075	0.7144	0.6454
With VD	0.0728	0.1940	0.1455
Velocity	δv_x [m/s]	δv_y [m/s]	δv_z [m/s]
Without VD	0.0579	0.0844	0.0429
With VD	0.0075	0.0141	0.0040
Attitude	$\delta\psi$ [°]	$\delta\theta$ [°]	$\delta\phi$ [°]
Without VD	0.0694	0.0710	0.0706
With VD	0.0553	0.0546	0.0581

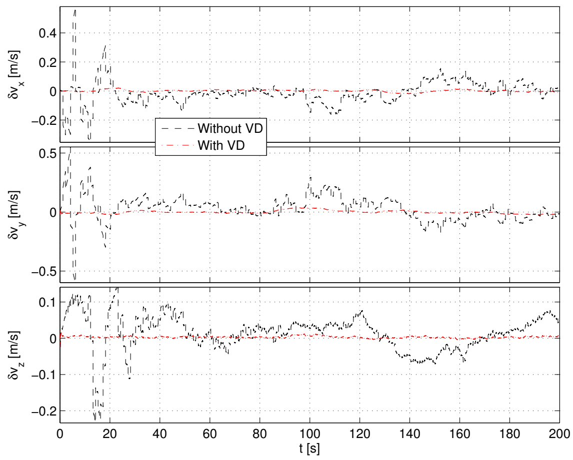

Fig. 6. Velocity estimation errors

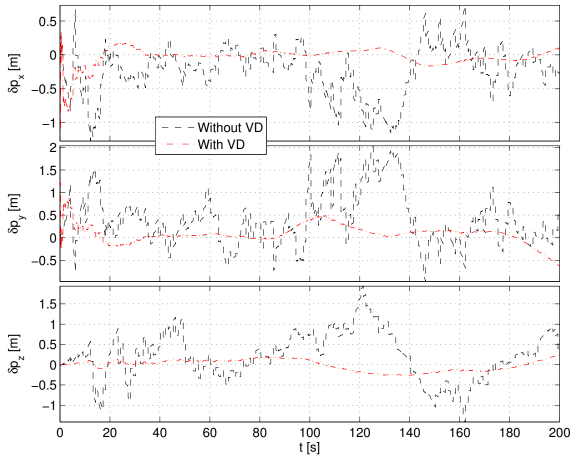

Fig. 7. Position estimation errors

Despite the promising results, the use of the VD model in real navigation systems must be addressed with appropriate care. As convincingly discussed in (Julier and Durrant-Whyte, 2003; Bryson and Sukkarieh, 2004), vehicle modeling errors (model simplification assumptions, over-parametrization of the model, unmodeled time-varying parameters), unmodeled dynamics, and perturbations such as vehicle load and underwater currents, may degrade the navigation system performance if not correctly taken into account.

6. CONCLUSIONS

A vehicle dynamics inclusion technique was successfully adopted in this paper to enhance position, velocity and attitude estimates of Inertial Navigations Systems. This type of INS aiding techniques step forward as an inexpensive software based solution that allows for a significant enhancement of the inertial estimates, as it was verified by the results of simulations performed. Future work on this subject will have its main focus on the implementation of the specific VD aiding solution developed in this paper on the on-board navigation system of the Infante vehicle property of ISR.

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