Positioning Monitoring Improvement in a Horizontal Plane INS by Using Fuzzy Logic Data Fusion for Denoising of Inertial Sensors in Redundant Clusters

Teodor Lucian Grigorie, Ruxandra Mihaela Botez

Abstract**—**The paper presents an application of fuzzy logic techniques in inertial navigation systems performance improvement, providing to the navigation processor denoised acceleration and angular speed data. For this purpose, some redundant clusters of sensors are used to sense acceleration or angular speed in each axis of the inertial measurement unit. The fuzzy logic denoising procedure fuses the data in each redundant detection cluster, being based on the idea that each sensor from an axis (measuring acceleration or angular speed) has a weight established in a fuzzy logic manner as a function of the standard deviation of the last m samples acquired from it. Starting from this procedure some experimental tests were performed by using a bi-dimensional INS navigator with a redundant MEMS inertial measurement unit, and an integrated GPS/INS navigator as reference positioning system. Each redundant cluster in the tested INS detection unit contains six sensors, having its sensitivity axes parallel and oriented in the same sense. The results show an important reduction of the navigation solution errors in comparison with the non-redundant navigation solutions obtained by the processing of the data provided to the navigation algorithm by the sensors having the same index in the clusters (it results six non-redundant INSs).

Keywords**—**denoising, fuzzy logic data fusion, inertial navigator, redundant detection unit.

I. Introduction

THE great part of the positioning technologies for modern navigation systems have been available for over three decades. During this period, inertial-navigation system (INS) and global positioning system (GPS) have been widely applied in many of this navigation applications. On the other way, besides the aerospace applications, the last two decades shown an increasing trend in the use of positioning and navigation technologies in land-vehicle applications ([1]-[3]).

The practice with all of this applications shown that, unfortunately, navigation accuracy and integrity of GPS are negatively affected when the navigation is performed in signal-degraded environments, when the satellite signals may get lost due to signal blockage ([4], [5]). With characteristics complementary to GPS, the INS has been widely adopted to assist GPS in a series of navigation systems, being able to address this problem and overcome the non-availability of GPS signals for a short period of time due to the inherent inertial sensors errors. Originally developed in the mid of 60s for Missile Guidance systems, INS has become an important component in military and scientific applications, at this time being standard equipment on most planes, ships, and submarines ([6]-[8]).

Having as a first advantage its dead-reckoning characteristic, the INS raises through its ability to provide the velocity and position of the vehicle with abundant dynamic information, due to the high calculation rate, and excellent short term performance. The main deficiency of the INS resides in its great accuracy degradation over time, due mainly to the used sensors performances, situation in what it can benefits from external aiding such as GPS ([3], [9]). More than that, this deficiency is accentuated today because of the rapid intrusion of miniaturization technologies (MEMS and NEMS) in inertial sensors manufacturing industry. These new technologies widely produce low-size and low-cost sensors, but unfortunately, with low performances, affected by noises and unstable values of biases and scale factors ([2], [6], [10], [11]). As a consequence, the today development of low-cost, small-size and high-precision INS/GPS navigators, suitable for positioning purposes in GPS challenging environments, oriented the researches in the following directions ([1], [3], [9], [12]-[14]): 1) development of standalone accurate strap-down miniaturized INS structures; 2) development of new INS/GPS data-fusion techniques incorporating artificial intelligence algorithms, in order to overcome the limitations in terms of model dependency, prior knowledge dependency, and linearization dependency.

The trend in the development of standalone accurate strap-down miniaturized INS structures is based on the improvement

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Teodor Lucian Grigorie is with the University of Craiova, Faculty of Electrical Engineering, Department of Electric, Energetic and Aerospace Engineering, 107 Decebal Blvd., 200440 Craiova, Dolj, Romania (phone: +40251436447; fax: +40251436447; e-mail: ltgrigorie@yahoo.com).

Ruxandra Mihaela Botez is with the École de Technologie Supérieure, Montreal, 1100 Notre Dame West, H3C 1K3, Montreal, Quebec, Canada (ruxandra.botez@etsmtl.ca).

of the quality of the inertial sensors or on the conception of new architectures and algorithms for sensors error estimation and compensation. It is very well known that the sensors noise is superimposed on the band 0-100 Hz of the navigation useful signal, which makes its filtering impossible ([10], [11], [15], [16]). Our identified way to perform the inertial sensors denoising is based on the elaboration of numerical algorithms, which fuse data from multiple sensors, grouped in redundant clusters in the same navigator, in order to provide a best estimate of the acceleration or angular speed signals. Based this consideration, we conceived a redundant architecture for the INS inertial measurement unit (IMU), considering, for each acceleration or angular speed component needed to be measured, a redundant cluster of inertial sensors having the sensitivity axes parallel and oriented in the same sense with the detection axis.

The here presented work was developed in a research project concerning the development of high-precision strap-down inertial navigators, based on the connection and adaptive integration of the nano and micro inertial sensors in low cost networks, with a high degree of redundance, financed by National Council for Scientific Research in Higher Education (CNCSIS) in Romania.

The proposed method uses fuzzy logic techniques to fuse the data in each redundant detection cluster, establishing for each of the sensors in the cluster a calculus weight as a function of the standard deviation of the last m samples acquired from it. To validate experimentally the algorithm, some tests were performed by using a bi-dimensional INS navigator structure with a redundant MEMS IMU, and an integrated GPS/INS navigator as reference positioning system. The redundant IMU was developed with three detection clusters, two for accelerations in x and y axes, and another one for the angular speed in z axis; each redundant cluster in the tested INS detection unit contains six sensors (Fig. 1). Paper exposes: 1) Data fusion method; 2) INS strap-down navigator mechanization; 3) Experimental results of the tested structure.

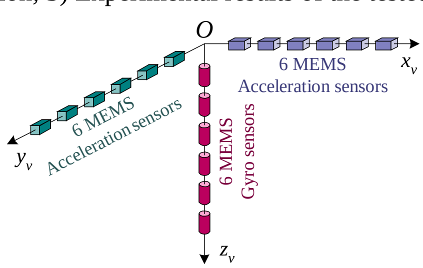

Fig. 1 IMU structure relative to vehicle frame

II. Data Fusion Method

In the following, we consider that each of the sensors redundant clusters in the IMU contains, in the general case, n collinear sensors. Denoting with x_i (i=1÷n) the measurements of the x quantity provided by the n sensors, with the σ_i (i=1÷n) standard deviations, then the data fusion algorithm combines these estimates under a weighted mean form in order to obtain an x_e estimate of the x quantity:

$$x_e = w_1 \cdot x_1 + w_2 \cdot x_2 + \ldots + w_n \cdot x_n = \sum_{i=1}^{n} w_i \cdot x_i,\ (\sum_{i=1}^{n} w_i = 1); \quad (1)$$

w_i (i=1÷n) are the weights of the x_i (i=1÷n) measurements. Our proposed methodology allows the dynamic establishment of the weights in a fuzzy logic manner, as a function of the standard deviation of the last m samples acquired from the sensors. In this way it is provided a degree of adaptability to the denoising mechanism. To develop a numerical structure able to calculate the sensors standard deviations at each time step, based on the last m acquired samples, a buffer should be used to have sensors data in repeated frames format. As a consequence, if m is the number of samples provided by each of the n sensors in one second, a FIFO (first in first out) buffer may be used to generate data frames of m consecutive samples; two consecutive frames are superposed with (m-1) samples ([15]). For each data frame, the standard deviations of the independent measurements are calculated with the next equation:

$$\sigma_i(k) = \sqrt{\frac{1}{m}\sum_{k=1}^{m}[x_i(k) - \bar{x}_i(k)]^2},\ i = (\overline{1,n}), \quad (2)$$

where: $x_i(k)$ is the k^{th} measurement from the i^{th} sensor and corresponds to the k^{th} data frame; $\sigma_i(k)$ is the standard deviation of the measurement x_i for the k^{th} data frame and will be used in "data fusion" for the next data frame; $\bar{x}_i(k)$ is the arithmetic mean of the m samples acquired from the i^{th} sensor in the k^{th} data frame,

$$\bar{x}_i(k) = \frac{1}{m}\sum_{k=1}^{m} x_i(k). \quad (3)$$

For each detection channel a fuzzy logic controller provides a weight $w_i^{fuzzy}(k)(i = \overline{1,n})$ as a function of the measured standard deviation $\sigma_i(k)$ of the m consecutive samples provided by the sensor in the k^{th} data frame. Therefore, the input of the controller is the standard deviation and the output is the sensor weight. To have the sum of all sensors weights in the detection array equal with 1, these are recalculated with the relations:

$$w_1(k) = \frac{w_1^{fuzzy}(k)}{\sum_{i=1}^{n} w_i^{fuzzy}(k)}, \cdots, w_n(k) = \frac{w_n^{fuzzy}(k)}{\sum_{i=1}^{n} w_i^{fuzzy}(k)}. \quad (4)$$

Finally, at the time t_{k+1} the x_e estimate of x is

$$\begin{aligned} x_e(k+1) &= w_1(k)\cdot x_1(k+1) + w_2(k)\cdot x_2(k+1) + \ldots + \\ &+ w_n(k)\cdot x_n(k+1) = \sum_{i=1}^{n} w_i(k)\cdot x_i(k+1),\ (\sum_{i=1}^{n} w_i(k) = 1). \end{aligned} \quad (5)$$

By resuming the previous statements, the data fusion architecture for the proposed algorithm can be organised as in Fig. 2. The chosen fuzzy logic controllers are by the "P" type, implementing some rules that creates a proportional dependence between the quality of the sensors signals and the associated weights that means an inverse proportionality between the calculated standard deviations and sensors associated weights. The structure of fuzzy controllers realized in Matlab/Simulink is presented in Fig. 3.

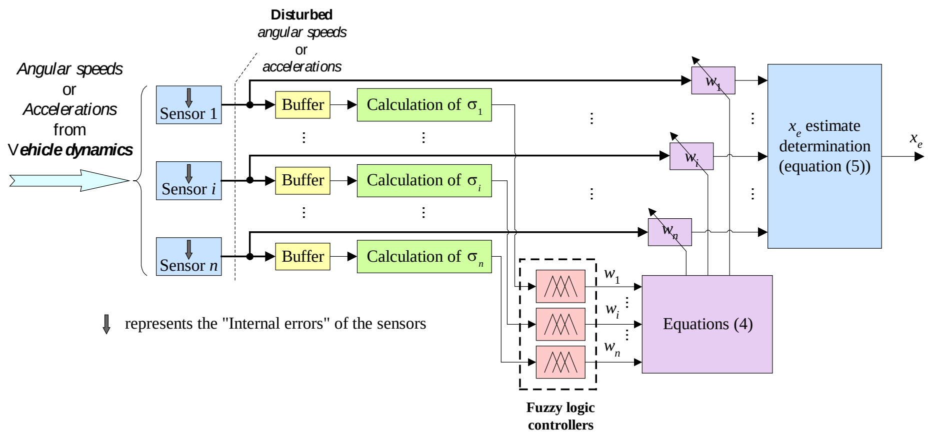

Fig. 2 Data fusion algorithm architecture

The membership functions for the fuzzification process were considered uniform distributed from 0 to 10, while for output were considered uniform distributed from 0 to 1. Both, input and output, where assigned with 9 membership functions by Gaussian type, distributed in the universes of discourse as in Fig. 4.

The associated fuzzification rules are: 1) *If* (std-dev is mf1) *then* (weight is mf9); 2) *If* (std-dev is mf2) *then* (weight is mf8); 3) *If* (std-dev is mf3) *then* (weight is mf7); 4) *If* (std-dev is mf4) *then* (weight is mf6); 5) *If* (std-dev is mf5) *then* (weight is mf5); 6) *If* (std-dev is mf6) *then* (weight is mf4); 7) *If* (std-dev is mf7) *then* (weight is mf3); 8) *If* (std-dev is mf8) *then* (weight is mf2); 9) *If* (std-dev is mf9) *then* (weight is mf1).

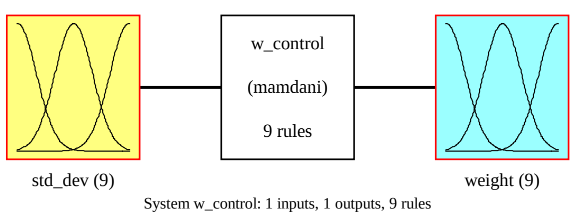

Fig. 3 Matlab/Simulink structure of fuzzy controllers

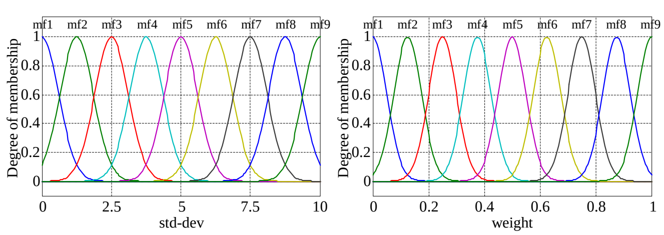

Fig. 4 *mf* for input and output

For the fuzzification process, the MAX-MIN inference method is used, while for defuzzification the centroid method is implied.

Based on our experimentally developed IMU architecture, with six sensors in each detection cluster, the equivalent Matlab/Simulink implementation of the data fusion algorithm in Fig. 5 is obtained. The block "Fuzzy-logic data fusion", in the right hand side of the figure, is obtained by grouping the model in the left hand side. Its inputs are the data obtained from the six sensors in the cluster "Si" (measurements x_i, i=1÷6), while its outputs are: fusion signal "S_f" (x_e estimate), sensors' assigned weights "w1-w6" (w_i, i=1÷6), standard deviation of the fusion signal "Std_f" (standard deviation of the x_e estimate), standard deviations of the data obtained from the six sensors "Std1-Std6" (standard deviations of the x_i (i=1÷6) measurements).

III. INS Strap-Down Navigator Mechanization

An IMU operating after the proposed method provide estimates of two accelerations and one angular speed through the processing of the signals obtained from two accelerometric and one gyrometric clusters.

Each of the three detection clusters contains six collinear sensors, providing independent estimates of the same acceleration or angular speed applied on respective axis. According to the mechanics principles applied in inertial navigation mechanisms, to find the position of a vehicle the general equation of navigation should be solved, relative to the navigation frame ([4], [8], [10], [11], [16]).

For our application, having in mind the need to navigate in horizontal plane, the kinematic acceleration $\vec{a}$ equals the specific force vector $\vec{f}$ (the accelerometers outputs) because the accelerometers outputs are not influenced by gravitation:

$$\vec{f} = \vec{a} = \frac{d\vec{v}}{dt} + \vec{\omega} \times \vec{v}; \qquad (6)$$

$\vec{v}$, $\vec{\omega}$ - vehicle absolute speed, and absolute angular speed.

To solve this equation it should be written in equivalent scalar form, relative to the vehicle frame, when we can evaluate a part of the variables based on the attached sensors, i.e. the accelerometers and gyros outputs. The equation solution provides the values of the vehicle absolute speed components relative to the axes of the vehicle frame. Therefore, the evaluation of the vehicle position and speed relative to the navigation frame requires an intermediary calculation step related to the speed components change from vehicle frame (eq. (6) solution) to navigation frame. To perform this step, the relative position of the two frame should be evaluated, i.e. the vehicle attitude.

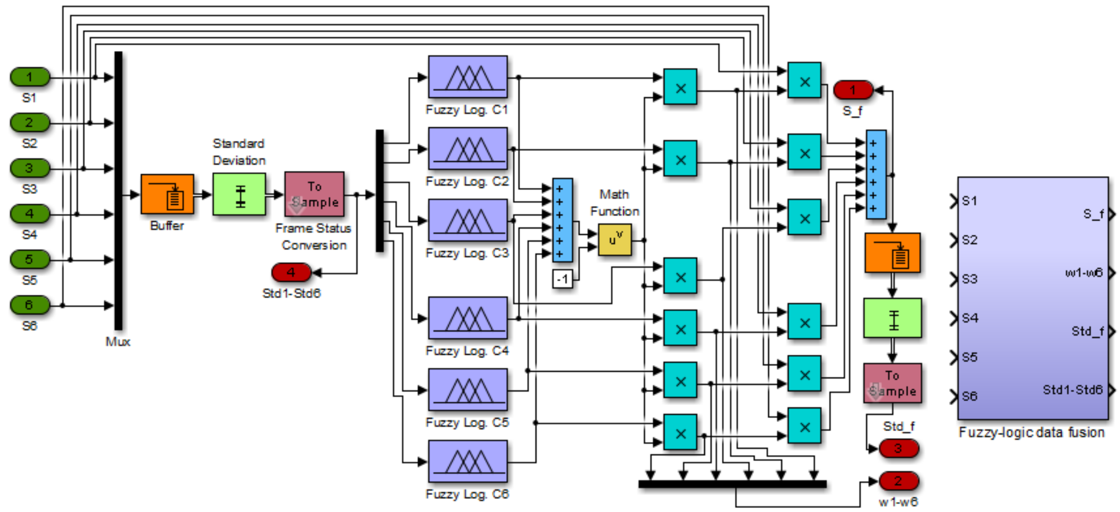

Fig. 5 Matlab/Simulink implementation of the data fusion algorithm

The proposed to be solved navigation problem conducts to the choosing of North-East-Down (NED - $Ox_l y_l z_l$) local horizontal frame as navigation frame. Adequate to the defined navigation frame, the next configuration is considered for the vehicle frame (SV - $Ox_v y_v z_v$): Ox_v axis along the vehicle' longitudinal axis, in front, Oz_v axis under the normal at Ox_v, in the vehicle' longitudinal plane, downward, and Oy_v axis in the right hand side of the vehicle, perpendicular to the $Ox_v z_v$ plane. Therefore, based on our positioning aim (horizontal-plane positioning), only the axes x and y are considered for the evaluation of the vehicle position and speed, while the vehicle attitude is characterized by the yaw angle, i.e. the rotation around the vertical axis z. Denoting with ω_{zv} the component of the angular speed ω along the z axis of the vehicle frame (the gyro reading), the yaw angle ψ results by its numerical integration as follows:

$$\psi = \psi_0 + \int_{t_{n-1}}^{t_n} \omega_{zv}\, \mathrm{d}t. \qquad (7)$$

where ψ_0 is the initial yaw angle value. Relative to the vehicle frame, eq. (6) equates the following scalar relations:

$$f_{xv} = \frac{\mathrm{d}\, v_{xv}}{\mathrm{d}\, t} + \omega_{zv} v_{yv}, \quad f_{yv} = \frac{\mathrm{d}\, v_{yv}}{\mathrm{d}\, t} - \omega_{zv} v_{xv}; \qquad (8)$$

f_{xv}, f_{yv} are the components of the specific force f in SV frame (accelerometric readings), and v_{xv}, v_{yv} - components of the speed v in SV frame. An easiest step of integration for eq. (8) leads to the values of the components v_{xv}, v_{yv}, which are further transformed in NED frame by using a particular coordinate change, rotation around the z axis, based only on the evaluated yaw angle:

$$\begin{bmatrix} v_{xl} \\ v_{yl} \end{bmatrix} = \begin{bmatrix} \cos\psi & -\sin\psi \\ \sin\psi & \cos\psi \end{bmatrix} \cdot \begin{bmatrix} v_{xv} \\ v_{yv} \end{bmatrix}. \qquad (9)$$

Based on the initial values x_{l0} and y_{l0} of the vehicle coordinates in North and East directions, the vehicle horizontal positioning is finally performed by using the equations:

$$x_l = x_{l0} + \int_{t_{n-1}}^{t_n} v_{xl}\, \mathrm{d}t, \quad y_l = y_{l0} + \int_{t_{n-1}}^{t_n} v_{yl}\, \mathrm{d}t. \qquad (10)$$

Implementing in Matlab/Simulink the navigator equations, the model in Fig. 6 is obtained.

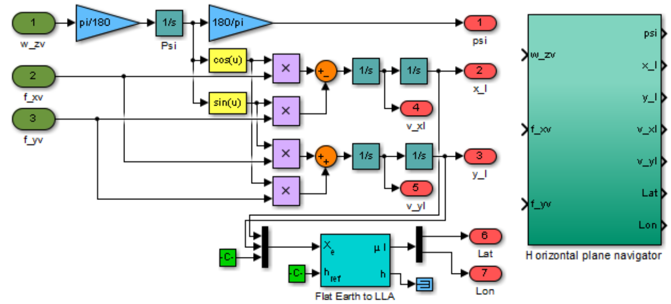

Fig. 6 Matlab/Simulink implementation of the navigation algorithm

To have driven distances, in North and East directions, in terms of latitude and longitude coordinates, the "Flat Earth to LLA" Matlab/Simulink block, making this conversion, is used in the model. The block "Horizontal plane navigator" in the right hand side of the figure results through the grouping of the model in the left hand side. Its inputs are the inertial measurements (accelerations in SV along the x and y axes, and angular speed in SV along the z axis), while its outputs are the yaw angle, the vehicle' position and speed relative to the navigation frame (in North and East directions), and the latitude and longitude coordinates.

IV. Experimental Results and Conclusions

To test experimentally the proposed methodology, were used *a redundant MEMS IMU (Inertial Measurement Unit)*, with three detection clusters (two accelerometric clusters and one gyrometric cluster) containing six sensors each, and *an integrated GPS/INS navigator* as reference positioning system. Both equipment were boarded on a test car, and operated in the same time.

The data acquired from the MEMS IMU sensors and the solution of navigation provided by the integrated GPS/INS navigator were further used to validate the proposed methodology for the positioning monitoring improvement by using fuzzy logic data fusion for denoising of inertial sensors.

The validation model, developed in Matlab/Simulink, is shown in Fig. 7. It includes: 1) three "Fuzzy-logic data fusion" blocks, used to fuse the acquired data in each of the three detection clusters; and 2) seven "Horizontal plane navigator" blocks, one of them used to process the filtered data provided by the three fusion blocks, and six of them used to process the data provided by the sensors having the same index in the three detection clusters (resulted one redundant INS and six non-redundant INSs).

The acquired data from the MEMS IMU is presented in Fig. 8 for the accelerometers in the *x* axis, in Fig. 9 for the accelerometers in the *y* axis, and in Fig. 10 for the gyros in *z* axis of the SV reference frame. The last graphical characteristic in each of the three figures represents the data fusion obtained signal for each of the three detection clusters.

The navigation solutions and associated errors for redundant INS with fuzzy logic data fusion, and for all of the six non-redundant INSs are presented in Fig. 11 to Fig. 17. The errors are calculated relative to the reference solution.

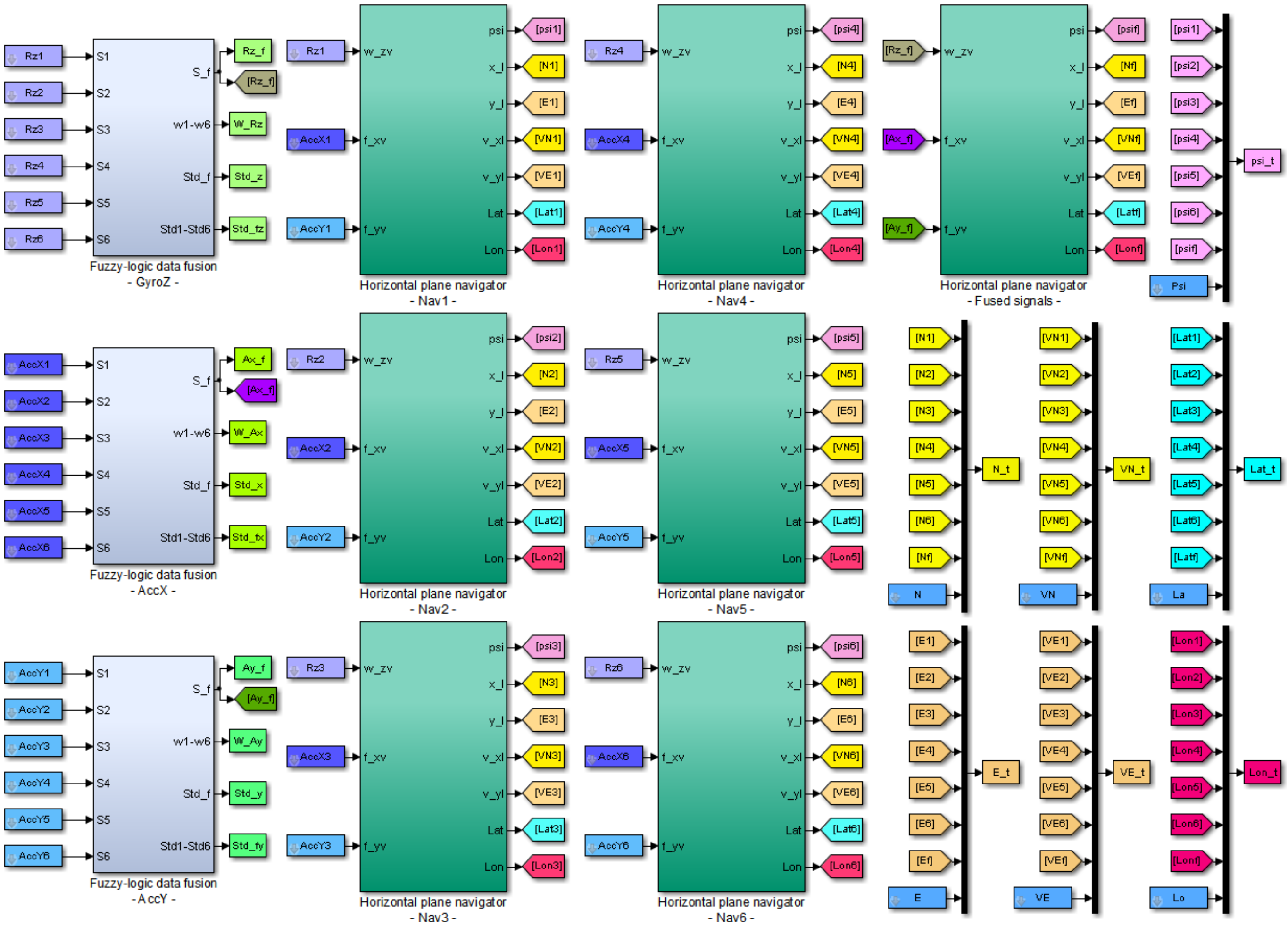

Fig. 7 Matlab/Simulink validation model

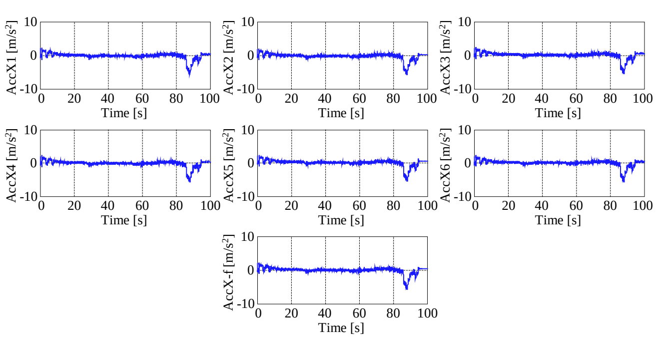

Fig. 8 Acquired data from the accelerometers in the *x* axis

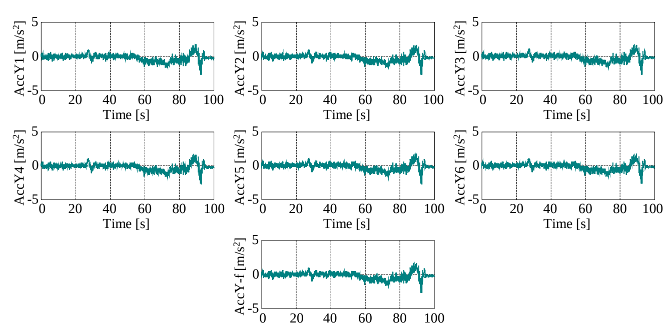

Fig. 9 Acquired data from the accelerometers in the *y* axis

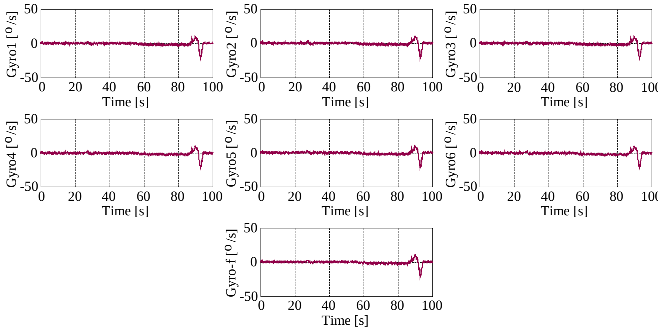

Fig. 10 Acquired data from the gyros in the *z* axis

The shown navigation solution components and errors are: the covered distances in the North direction (Fig. 11), the covered distances in East direction (Fig. 12), the yaw angles values (Fig. 13), the speed values in the North direction (Fig. 14), the speed values in the East direction (Fig. 15), the vehicle Latitude coordinates (Fig. 16), and the vehicle Longitude coordinates (Fig. 17). The trajectories of the vehicle in horizontal plane is presented in the left hand side of the Fig. 18 (Latitude versus Longitude), while the deviations from the reference trajectory calculated by redundant INS and the six non-redundant INSs are exposed in the right hand side of Fig.18 (Latitude errors versus Longitude errors).

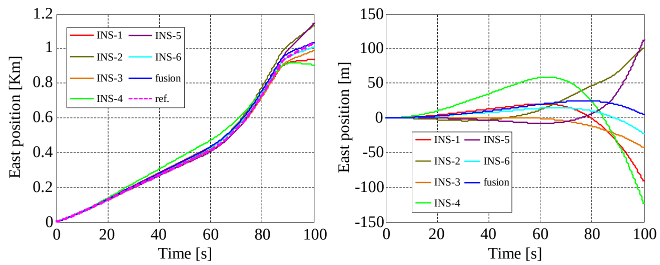

Fig. 12 East positions and errors

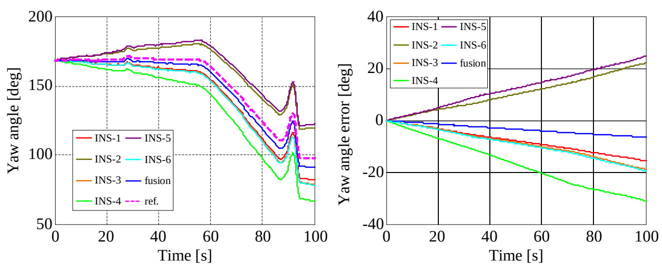

Fig. 13 Yaw angle values and errors

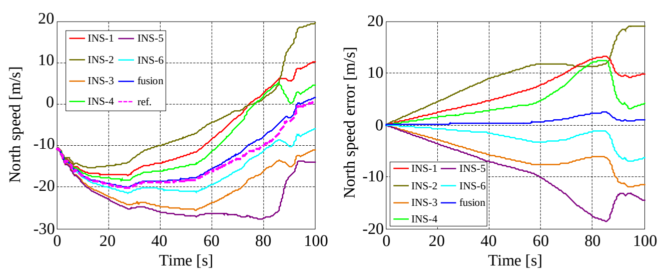

Fig. 14 North speed and errors

The evolution in time of the vehicle, estimated by the redundant system and by the six non-redundant INSs is shown in Fig. 19 (Latitude vs. Longitude vs. time), while the deviations from the reference trajectory in time are exposed in Fig. 20 (Latitude errors vs. Longitude errors vs. time).

Evaluating the absolute maximum values of the navigation solution errors in all of the seven tested navigators, the values in Table I were obtained. The blue values assign the best cases (minimum values of these errors), while the red ones assign the worst cases (maximum values of these errors).

It can be easily observed that the best cases are associated to the redundant INS, excepting two situations corresponding to the green values (East position and Longitude position); should be mentioned that the two green values are very close to the blue values in East and Longitude components, found for INS6.

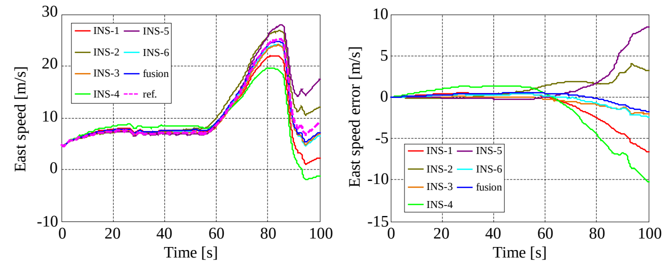

Fig. 15 East speed and errors

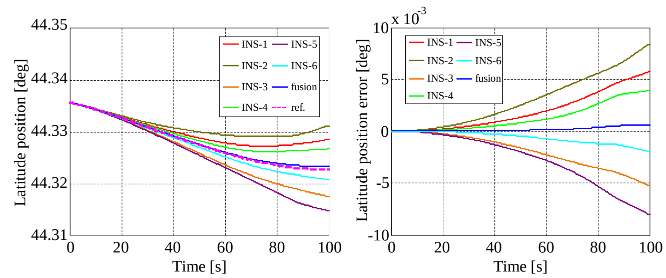

Fig. 16 Latitude coordinates and errors

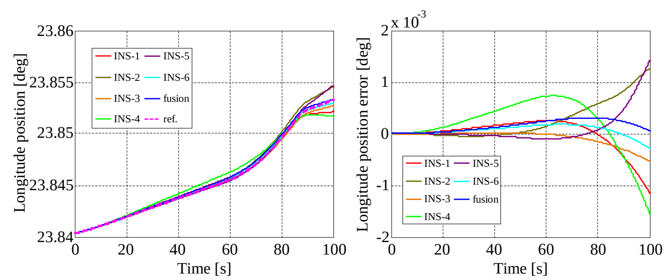

Fig. 17 Longitude coordinates and errors

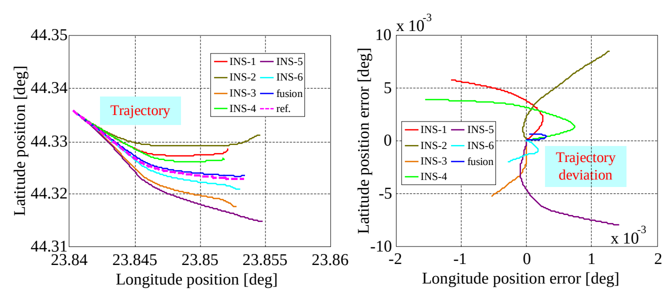

Fig. 18 Trajectories of the vehicle in horizontal plane and deviations from the reference trajectory

Table I. Errors analysis

Abs. max error	INS1	INS2	INS3	INS4	INS5	INS6	Fusion	Mean value	Mean/Fus.	Max/Fus.	Min/Fus.
North [m]	634.5045	**931.0303**	581.5833	433.7669	891.0633	220.4880	**69.2359**	615.4061	8.8885	13.4472	3.1845
East [m]	91.3747	100.4168	42.2389	**122.9860**	111.9274	**21.9566**	**24.5774**	81.8167	3.3289	5.0040	0.8933
V-North [m/s]	13.1621	**19.1634**	12.0308	12.4389	18.5365	7.0859	**2.3972**	13.7362	5.7302	7.9942	2.9559
V-East [m/s]	6.6277	3.9710	2.0468	**10.2027**	8.4689	2.3690	**1.7420**	5.6143	3.2229	5.8569	1.1749
Latitude [deg]	$57.101 \cdot 10^{-4}$	$\mathbf{83.786 \cdot 10^{-4}}$	$52.338 \cdot 10^{-4}$	$39.036 \cdot 10^{-4}$	$80.190 \cdot 10^{-4}$	$19.842 \cdot 10^{-4}$	$\mathbf{6.230 \cdot 10^{-4}}$	$55.382 \cdot 10^{-4}$	8.8885	13.4472	3.1849
Longitude [deg]	$11.457 \cdot 10^{-4}$	$12.591 \cdot 10^{-4}$	$5.296 \cdot 10^{-4}$	$\mathbf{15.420 \cdot 10^{-4}}$	$14.034 \cdot 10^{-4}$	$\mathbf{2.753 \cdot 10^{-4}}$	$\mathbf{3.081 \cdot 10^{-4}}$	$10.258 \cdot 10^{-4}$	3.3289	5.0040	0.8935
Yaw [deg]	15.6123	22.2271	18.7895	**31.1004**	24.9227	19.4310	**6.4500**	22.0138	3.4130	4.8217	2.4205

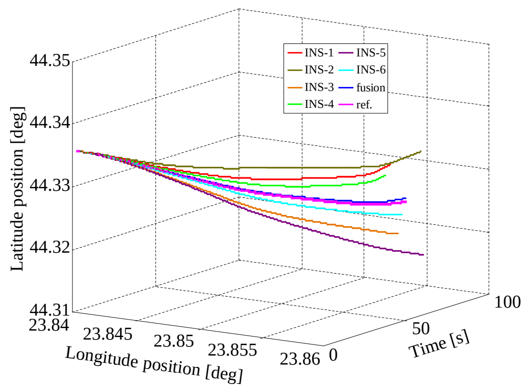

Fig. 19 The evolution in time of the vehicle

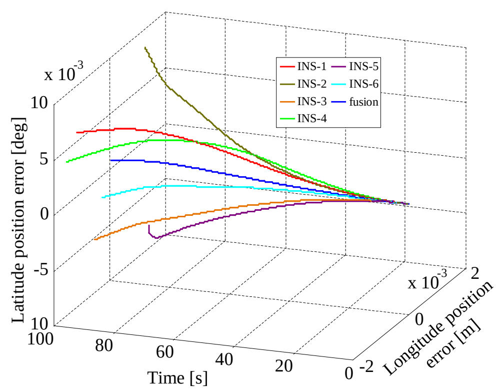

Fig. 20 The deviations from the reference trajectory in time

Table I presents also the mean values for these errors in each channel of the navigation solution (North position, East position, North speed, East speed, Latitude, Longitude, Yaw angle) and the next ratios: 1) ratio between the mean values of the absolute maximal values of the errors, and the absolute maximal values of the errors corresponding to the fusion case; 2) ratio between the maximal values of the absolute maximal values of the errors, and the absolute maximal values of the errors corresponding to the fusion case; 3) ratio between the minimum values of the absolute maximal values of the errors, and the absolute maximal values of the errors corresponding to the fusion case.

Starting from the comparative graphical results, correlated with the numerical values presented in Table I, we can conclude an important positioning precision improvement by using the proposed data fusion methodology for inertial sensors. It is shown an important reduction of the navigation solution errors in comparison with the non-redundant navigation solutions obtained by the processing of the data provided to the navigation algorithm by the sensors having the same index in the clusters (it results six non-redundant INSs).

The numerical values prove a reduction of the medium level of the absolute maximal values of the errors of about 8.8 times in the North position channel, 3.3 times in East position channel, 5.7 times in North speed channel, 3.2 times in East speed channel, and 3.4 times in attitude channel (yaw angle). It should be mentioned that no previous calibration procedure was applied to the inertial sensors connected in the redundant MEMS IMU; the sensors biases are uncompensated. The absolute maximal values of errors, after 100 s of positioning with the redundant IND based fuzzy logic data fusion, are: 69.23 m in North position, 27.57 m in East position, 2.39 m/s in North speed, 1.74 m/s in East speed, $6.230 \cdot 10^{-4}$ deg in Latitude, $3.081 \cdot 10^{-4}$ deg in Longitude, and 6.45 deg in Yaw angle.

The best configuration for the non-redundant INSs is for the 6th sensor in the detection clusters, the results for this one and for the proposed configuration being very close in the East position channel, corresponding also to the Longitude position channel. At the level of the other channels are noted also performance improvements brought by proposed redundant configuration: reduction of 3.18 times of the North position absolute maximal values of errors, reduction of 2.95 times of the North speed absolute maximal values of errors, reduction of 1.17 times of the East speed absolute maximal values of errors, reduction of 3.18 times of the Latitude absolute maximal values of errors, and reduction of 2.42 times of the yaw angle absolute maximal values of errors.

The worst configurations for the non-redundant INSs are for the 2nd, respectively 4th, sensor in the detection clusters. For INS2 are obtained the worst values for the absolute maximal values of errors in North position channel (931.03 m), in North speed channel (19.16 m/s), respectively in the Latitude position channel ($83.78 \cdot 10^{-4}$ deg). For INS4 are obtained the worst values for the absolute maximal values of errors in East position channel (122.98 m), in East speed channel (10.2 m/s), in the Longitude channel ($15.42 \cdot 10^{-4}$ deg), respectively in the yaw angle channel (31.04 deg).

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