Fuzzy Corrections in a GPS/INS Hybrid Navigation System

ADRIAN HILIUTA
RENÉ JR. LANDRY
FRANÇOIS GAGNON, Senior Member, IEEE
École de Technologie Supérieure
Montréal

A new concept regarding GPS/INS integration, based on artificial intelligence, i.e. adaptive neuro-fuzzy inference system (ANFIS) is presented. The GPS is used as reference during the time it is available. The data from GPS and inertial navigation system (INS) are used to build a structured knowledge base consisting of behavior of the INS in some special scenarios of vehicle motion. With the same data, the proposed fuzzy system is trained to obtain the corrected navigation data. In the absence of the GPS information, the system will perform its task only with the data from INS and with the fuzzy correction algorithm. This paper shows, using Matlab simulations, that as long as the GPS unavailability time is no longer than the previous training time and for the scenarios a priori defined, the accuracy of trained ANFIS, in absence of data from a reference navigation system, is better than the accuracy of stand-alone INS. The flexibility of model is also analyzed.

Manuscript received April 15, 2003; revised August 30, 2003; released for publication January 9, 2004.

IEEE Log No. T-AES/40/2/828679.

Refereeing of this contribution was handled by M. G. Simões.

Authors' address: Dept. of Electrical Engineering, École de Technologie Supérieure, 1100 Notre Dame West St., Montréal, PQ, Canada H3C 1K3, E-mail: (ahiliuta@ele.etsmtl.ca).

I. INTRODUCTION

The vulnerabilities of GPS are related to intentional disruption of the service, as invoked in [1], to the loss of accuracy in the narrow-street environment [2], because of a poor geometrical-dilution-of-precision (GDOP) coefficient and to the multipath reflection. The presence of noise in GPS signals compels the use of narrow bandwidth filters, which limits also the dynamic of the vehicle [3]. Because a satellite navigation system, either GPS or GNSS, is not autonomous, it is suitable to integrate this type of navigation system with a different system, which should procure a greater autonomy. From this point of view, the inertial navigation system (INS) is ideal. In opposition with receiving signals from satellites, in the case of GPS, the autonomy of INS is provided by the functioning principle, which is based on measurements of inertia of the vehicle, linear accelerations, and angular velocities. The main interest is the position determination, which is possible after a double integration of the accelerations to obtain linear displacements and a single integration of the angular velocities to obtain the angles of rotation. The use of this integration process implies that a small uncertainty in measurement bias become a position error that grows with time [4].

INS provides self-contained independent means for three-dimensional positioning with high short-term accuracy [5, 6]. The INS accuracy degrades over time, due to the unbounded positioning errors caused by the uncompensated gyro and accelerometer errors affecting the INS measurements. The degradation is much faster for low-cost INS systems. INS provides high-accuracy three-dimensional positioning when the GPS positioning is poor or unavailable over short periods of time (e.g., due to poor satellite geometry, high electromagnetic interference, high multipath environments, or obstructed satellite signals). In addition, the INS system provides much higher update positioning rates compared with the output rate conventionally available from GPS. High-accuracy INS units, e.g., Litton LN-100 [7], provide attitude determination at the level of 1–3 arcmin. Updating INS with GPS positions will provide the system's orientation at ~ 30 arcsec level. The development of INS technology will allow us to the reach, in the next 5 to 10 years, a level of error up to 0.2 nmi/hr within 90% circular error probability (CEP) for aircraft, vehicle, or spacecraft for attitude, guidance, and control, as it is estimated in [8]. The same parameter for ships will be up to 1 nmi in 30 hrs, and for missiles up to 0.8 nmi/hr. Integration of GPS with INS bounds the positioning errors of the inertial system with the uniform positioning errors affecting the GPS system. These errors depend on the systematic and random errors affecting the GPS measurements, as amplified by the satellite geometry. Using the GPS positions, the GPS/INS integration filter can estimate the error states affecting the INS measurements. These error state estimates are used to calibrate the INS system on a continuous basis. The high accuracy of the INS system over short periods of time allows correction of undetected cycle-slips affecting the GPS measurements.

There are two basic GPS/INS integration schemes: loosely (or cascaded or modular) and tightly coupled mode [9]. In the loosely coupled mode, the GPS receiver and the INS are treated as separate navigation systems. The GPS receiver contains a filter, which processes the raw GPS observables and supplies a position, velocity, and time solution. The INS implements its navigation/attitude algorithms to give a position, velocity, and attitude. An integrated Kalman filter (KF) is then applied to combine the GPS and INS solutions. In the tightly coupled mode, however, only a single KF is applied to process both sets of sensor data: raw GPS code/phase observations and INS measurements.

The integration between GPS and INS exploits their synergy in various approaches, based on the use of KF, with the goal to mitigate the short time error of GPS and long time error of INS [10, 11]. The resulting plant is a combined navigation system that has better performances than GPS or INS, considered as stand-alone navigation systems. The KF properties are well understood and analytically proven, and it is not the purpose of this paper to reiterate the KF functioning principle. However, we have to underline that, in order to calculate the estimate of INS error, KF constantly needs information from both sources: INS and GPS. Based on INS autonomy, we assume that it will be always available to provide KF with data. On the other hand, the normal performance of GPS can be disrupted [1], case in which the accuracy of integrated navigation system will decay to stand-alone INS accuracy. Some attempts to use fuzzy logic in navigation were made for GPS code and carrier-phase measurements [12] or for adaptive tuning of KF in GPS/INS integrated navigation systems [13, 14].

In the attempt to prevent or, at least, to reduce the impact of accuracy decreasing when GPS becomes unavailable, we used an adaptive neuro-fuzzy inference system (ANFIS), built and trained using data from stand-alone INS, on one hand, and from the most accurate navigation system available, considered as reference, on the other hand. The issue is to prove that, with an appropriate choice of parameters, the ANFIS can be built and trained during the availability time of reference system. We show, in the following pages, that passing the INS data through ANFIS will procure a better accuracy when the reference source is missing. The errors and the flexibility of the system will be analyzed.

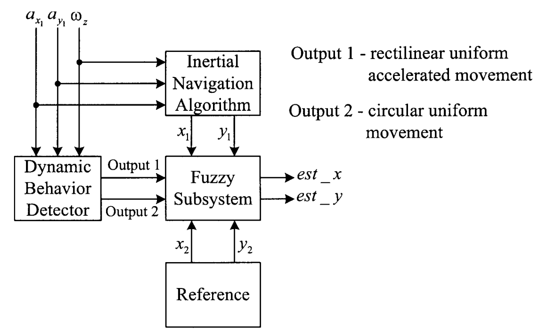


Fig. 1. Schematics of fuzzy integrated navigation system.

II. PROPOSED SCENARIOS

The movement of a vehicle can be regarded as a composition of several basic motions along and/or around the three axes. Due to the similarities of approaches, no matter what basic motion we choose for demonstration purpose, we propose here only one scenario, as well as a possibility to switch and/or to combine several scenarios using dynamic behavior detector (Fig. 1). During simulation process, we evaluate also how much the real data can differ from the training data, this having implications in the number of scenarios to be considered in order to describe the entire motion of the vehicle.

We have chosen a simple case to demonstrate the concept of use of structured knowledge bases, but it is also, the most commonly used and that addresses the largest market. It is a 2D navigation system in which the lateral accelerations are induced only by the angular velocity and not by a real lateral displacement of the vehicle. This is the typical ground transportation scenario.

In this study, we assume the following basic scenarios that determine the values of acceleration upon the vehicle orientation axis (a_x) and angular velocity upon the vertical axis (ω_z):

1) rectilinear uniform accelerated movement: constant a_x and $\omega_z = 0$,

2) circular uniform movement $a_x = 0$ and constant ω_z.

This approach is nothing else but the use of dynamic behavior of the vehicle in implementation of the navigation algorithm, as it was used in [15]. The difference consists in the way the dynamic behavior of the vehicle is described. In [15], the model is stochastic and differential equations driven by random noise are used. In our research, the use of a heuristic model of the vehicle, rather than a deterministic one, is investigated. The deterministic model is assumed to be completely described by differential equations. The heuristic model is built on trial-and-error methods.

In Fig. 1, we can observe the structure of such system. The dynamic behavior detector and inertial navigation algorithm process the raw inertial data. The

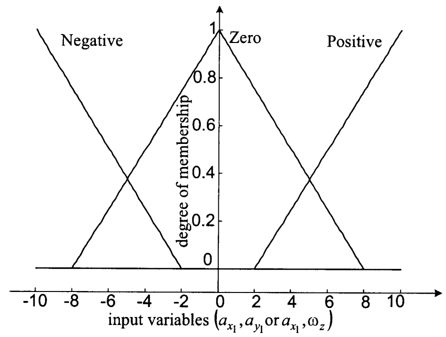


Fig. 2. Membership functions at inputs of dynamic behavior detector.

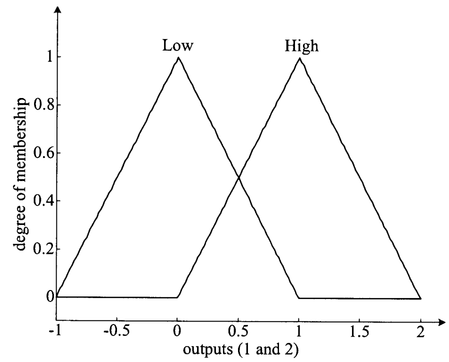


Fig. 3. Membership functions at outputs of dynamic behavior detector.

first is used to detect which of the two scenarios is currently under way according to the input data.

The reference data provided by the reference block in Fig. 1 are used for building and training the ANFIS in the fuzzy subsystem block. The training data have to be as accurate as possible and are necessary only during the training process. Part of the data will be used to check the accuracy of training. The role of fuzzy subsystem is to correct the errors of stand-alone INS, taking into account the dynamic of the movement of the vehicle, as well as the information stored as ANFIS, built and trained during the availability of the reference source. We have to mention that the output of reference system (that can be GPS or GPS/INS KF integrated system) is used to provide navigational data as long as these are available.

It is obvious that, in the actual case, we do not have a clear delimitation between both scenarios. Rather than crisp values, at the outputs of this block, we have two weighted coefficients, with values between 0 and 1. We can obtain noncrisp values at the outputs by using a fuzzy dynamic behavior detector. The proposed input membership functions are shown in Fig. 2, and the output membership functions in Fig. 3.

The values for the input variables are given only as example, and they have to be established according to the dynamic of the vehicle. For each variable, the inference rules, stored in fuzzy associative memory (FAM), are as follows.

1) If (input variable is negative) then (output is high) (1).
2) If (input variable is zero) then (output is low) (1).
3) If (input variable is positive) then (output is high) (1).

The input membership functions are used to transform the crisp values of the input variables in a linguistic degree (Fig. 4).

As example, in the same figure, the value 4 of the input variable is "zero" in a degree of 0.5 and "positive" in a degree of 0.25. The process is called fuzzification. After obtaining of the linguistic values of variables, we can do the inference, on the basis of rules. The linguistic value "zero" activates the rule number 2 (see the rules above), while the linguistic value "positive" activates the rule number 3. The inference process consists in obtaining of conclusions from premises, during the evaluation of rules stored in a FAM. In this manner, the inference process that uses the second rule gives an activation of the "low" value of the output coefficient. In the same way, the inference process that uses the third rule leads to the activation of "high" value. The evaluation process leads to activation of an output membership

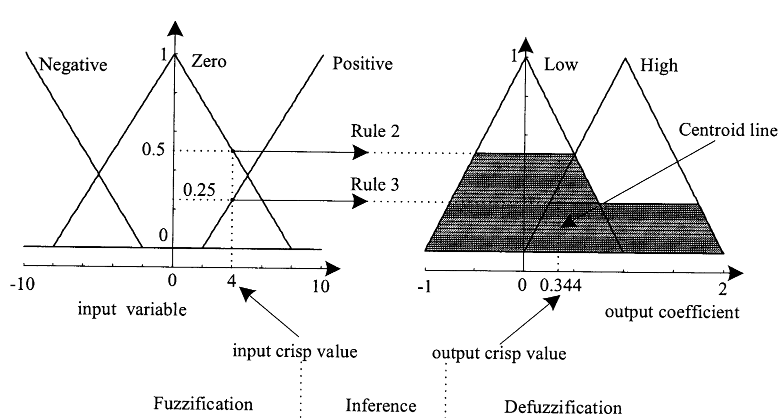


Fig. 4. Fuzzification, inference and defuzzification processes.

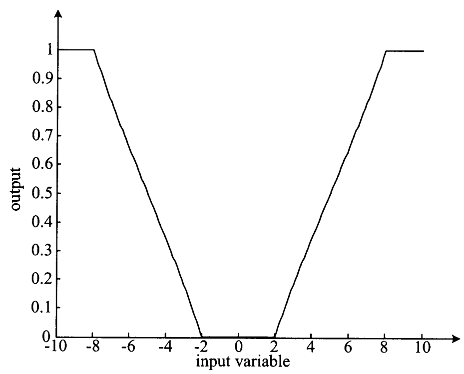


Fig. 5. Output of dynamic behavior detector as function by corresponding input values.

function, in a degree corresponding to fuzzification and inference process. The union of all the activated membership functions gives a 2D figure, for which the horizontal coordinate of the center of gravity is the crisp value of the output of the system. This process is called defuzzification.

Mapping each output as function of each input will lead to the graphic representation from Fig. 5. The points in which the saturation limits are reached are modifiable by modification of the membership functions from Fig. 2 and 3. This kind of approach for dynamic behavior detector permits to select not only the studied cases, but the subcases as well: small constant a_x and $\omega_z = 0$; medium constant a_x and $\omega_z = 0$, and so on. The output coefficient permits the obtaining of the final position as the weighted average of results in each basic scenario that is activated and to appreciate the degree in which each scenario is satisfied. The output of dynamic behavior detector shows if the input variable has a variation over time, and if this variation is large enough to take into consideration the corresponding scenario. The intermediate values for input variables cause an output coefficient between 0 and 1, while large values cause an output with the value equals to 1. In this manner, the output coefficient is used to weight the decision about the scenario to be considered.

III. INERTIAL NAVIGATION ALGORITHM FOR PROPOSED SCENARIO

The two reference frames used to compute the position (Fig. 6) are: a fixed one (xOy), attached to a point on the Earth's surface; the mobile one ($x_1O_1y_1$), attached to the vehicle. The axis O_1x_1 is the longitudinal axis of terrestrial vehicle and O_1y_1 is the perpendicular axis, in the horizontal plane. The center O_1 is the center of inertial navigation system.

The vehicle movement is uniquely determined by the acceleration a_{x_1}. The velocity of vehicle is

$$v_{x_1} = \int a_{x_1} dt. \qquad (1)$$

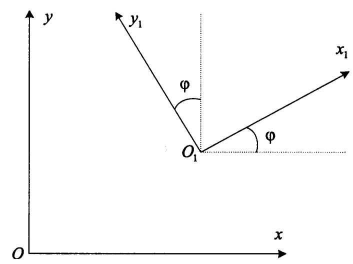


Fig. 6. Reference frames.

In the frame xOy, since there is no lateral movement, in the scenario that makes the object of this analyze ($v_{y_1} = 0$), the vehicle is moving with velocities:

$$\begin{cases} v_x = v_{x_1}\cos\varphi \\ v_y = v_{x_1}\sin\varphi \end{cases} \qquad (2)$$

where φ is

$$\varphi = \int \omega_z dt. \qquad (3)$$

The vehicle displacements, with respect to the departure point, in the fixed frame, are

$$\begin{cases} x = \int v_x dt \\ y = \int v_y dt \end{cases}. \qquad (4)$$

The angle φ is obtained from the angular velocity ω_z or from the measurements of acceleration. In fact, in the terrestrial vehicle scenario, the lateral acceleration is induced only by the angular movement, with the angular velocity ω_z, along a trajectory with a radius r. Such acceleration is given by

$$a_{y_1} = \omega_z^2 r. \qquad (5)$$

The radius of curve depends on the speed of the vehicle and on its angular velocity:

$$r = \frac{v_{x_1}}{\omega_z} = \frac{\int a_{x_1} dt}{\omega_z}. \qquad (6)$$

Replacing in (5), we obtain

$$a_{y_1} = \omega_z^2 \frac{\int a_{x_1} dt}{\omega_z} = \omega_z \int a_{x_1} dt \qquad (7)$$

from which we can calculate

$$\omega_z = \frac{a_{y_1}}{\int a_{x_1} dt}. \qquad (8)$$

Thus, the angle φ is given by

$$\varphi = \int \omega_z dt = \int \left[\frac{a_{y_1}}{\int a_{x_1} dt}\right] dt. \qquad (9)$$

In conclusion, using the measurements a_{x_1}, a_{y_1} and equations in the order of (4), (2), (9), and (1), or the measurements a_{x_1}, ω_z and the equations in the order of (4), (2), (3), and (1), we are able to calculate the position displacement of the mobile.

IV. FUZZY SUBSYSTEM

The accelerometers and gyrometers mainly produce two types of errors. The first type is a random process, at high frequency and following a Gaussian distribution with zero-average and variance σ^2. The second type is a bias that varies slowly (low frequency). However, the data from transducers are integrated in inertial navigation algorithm and the high frequency noise, the first type of error, can be greatly reduced. The second error, integrated over time, is the main cause for the rise of position error in INS. If this bias is small and slowly variable, then it can be compensated using the artificial intelligence technique. In this section, the methodology of use of ANFIS [16] as a training technique in inertial navigation is described. As stated in [8], current methods of data fusion are: extended Kalman filtering, model-based approaches, wavelet decomposition, artificial neural networks, and fuzzy logic. The methods developed in the field of artificial intelligence include the following: common-sense reasoning, nonmonotonic logic, circumspection, algorithms used in neural networks, and extension to Bayesian calculi. Further research and development is needed to develop the capacity to reason in the face of uncertainty and to fuse information from disparate sources.

When the GPS is available and has a good GDOP coefficient, the GPS position data are used to form the output vector of the fuzzy subsystem. The two inputs will be formed with the INS position data and, respectively, with a delayed (with one step) variant of these data. Consequently, the input-output training pairs are: position reported by stand-alone INS (first input), the same data delayed with one step (second input), and the position as reported by the reference navigation system (the output during the training and the aim of ANFIS when the data from this system are not available). In this way, we take into account the INS data, the variation of these data and the data from GPS. Matlab is used to generate and train an ANFIS. The training aims the parameters of the membership functions and is done using a back propagation algorithm either alone or in combination with a least squares method. In our assumption, the training objective is to minimize the absolute position error, defined as difference of the reference position and the position reported by stand-alone INS. During the training process, the fuzzy subsystem learns about the evolution of INS errors in different situations. The resulting model is heuristic and, as we mentioned before, is built on trial-and-error method.

To generate a data set, for use in the training of fuzzy subsystem, we have imagined a linear trajectory. The vehicle starts with $a_{x_1} = 2$ m/s^2 and keeps this acceleration during 10 s; it reaches the speed $v_{x_1} =$ 20 m/s; after that, the vehicle goes with constant speed until $t = 100$ s; therefore, the total equivalent distance will be $x_1 = 100$ m + 1800 m = 1900 m.

The INS model used in the simulations is built with models of two accelerometers ADXL 105, mounted on the axes O_1x_1 and O_1y_1, respectively. The models are developed in Simulink with data from producer data sheet. Additionally, sensors orientation errors can be added, to simulate mounting errors. The position is calculated as explained in Section II of this paper. The samples of reference signal, as well as those of signals from INS, are every 0.1 s. To build and train the ANFIS, first, and to evaluate navigation errors afterwards, we have used the following parameters and equations.

1) the reference position and velocity on Ox axis, x and v_x;

2) the reference position and velocity on Oy axis, y and v_y;

3) the position and velocity reported by stand-alone INS on Ox axis, x_i and v_{x_i};

4) the position and velocity reported by stand-alone INS on Oy axis, y_i and v_{y_i};

5) the relative position error of INS is calculated using

$$e_1 = \frac{\sqrt{(x-x_i)^2 + (y-y_i)^2}}{\sqrt{x^2+y^2}} \cdot 100(\%) \tag{10}$$

6) the absolute velocity error is calculated using

$$e_{v_1} = \sqrt{v_x^2 + v_y^2} - \sqrt{v_{x_i}^2 + v_{y_i}^2} \tag{11}$$

7) the angle between the vehicle velocity and the Ox axis, reported by the reference system (GPS), is given by

$$\varphi = \arctan \frac{v_y}{v_x} \tag{12}$$

8) the angle between the vehicle velocity and the Ox axis, reported by INS, is given by

$$\varphi_i = \arctan \frac{v_{y_i}}{v_{x_i}} \tag{13}$$

9) the absolute error of angle was calculated with

$$e_{\varphi_1} = \varphi - \varphi_i \tag{14}$$

10) using ANFIS, the positions on Ox axis ($\hat{x}$) and on Oy axis ($\hat{y}$) were estimated;

11) the estimation of velocities are

$$\hat{v}_x = \frac{d\hat{x}}{dt} \qquad \hat{v}_y = \frac{d\hat{y}}{dt} \tag{15}$$

12) the estimation of angle is

$$\hat{\varphi} = \arctan \frac{\hat{v}_y}{\hat{v}_x} \tag{16}$$

TABLE I
Simulation Results in Case of 2-rules ANFIS

Case	INS Position Error e_1 [%]	Estimator Position Error e_2 [%]	INS Velocity Error e_{v_1} [m/s]	Estimator Velocity Error e_{v_2} [m/s]	INS Angle Error e_{φ_1} [°]	Estimator Angle Error e_{φ_2} [°]	Length of Simulation [s]
1	4.2	0.6	−0.83	0.11	−4.2	0	100
2	1.88	0.05	−0.28	0.01	−0.63	0	50
3	1.45	1.2	−0.25	−0.28	−0.24	0	50
4	2.11	7.45	−0.13	4.3	−0.93	0	50
5	2.78	0.64	−0.27	−0.37	−2.11	0	50
6	2.12	1.82	−0.29	1.7	−0.87	0	50
7	2.81	0.05	−0.29	0.02	−2.03	0	50
8	2.71	0.64	−0.17	0.12	−1.92	0	50
9	2.05	0.7	−0.16	0.12	−0.74	0	50
10	2.8	0.64	−0.14	0.02	−2.05	0	50

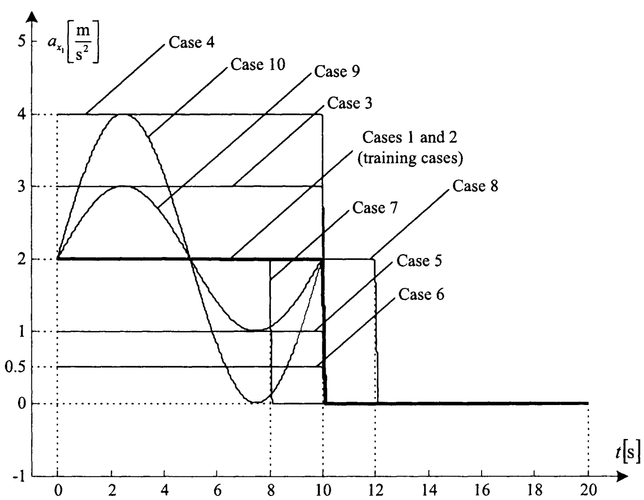


Fig. 7. Ten cases of input acceleration.

13) the estimation error in position is

$$e_2 = \frac{\sqrt{(x-\hat{x})^2 + (y-\hat{y})^2}}{\sqrt{x^2+y^2}} \cdot 100(\%)$$

in velocity is

$$e_{v_2} = \sqrt{v_x^2 + v_y^2} - \sqrt{\hat{v}_x^2 + \hat{v}_y^2} \tag{17}$$

in angle is

$$e_{\varphi_2} = \varphi - \hat{\varphi}.$$

Using these suppositions and formulas, a set of simulations was made, in order to establish the limits of possibilities to use ANFIS in correction of the INS errors. The simulations were made in different situations in which the initial accelerate motion was 3 m/s^2 or 1 m/s^2, during 8 s or 12 s, for constant or variable acceleration, positive or negative (Fig. 7). In total, ten cases were studied for each fuzzy system, each having up to 7 rules. The results for 2-rules ANFIS are presented in Table I.

To synthesize the results of Table I, the average and the standard deviation for the data in the two first columns were calculated. For the first column, the following values were obtained: $m_1 = 2.491\%$ and $\sigma_1 = 0.759\%$. For the second: $m_2 = 1.379\%$ and $\sigma_2 = 2.194\%$.

The average of errors in ANFIS case is about two times smaller than the stand-alone INS, but the standard deviation is larger. If we look into the Table I, we can see the source of this large variation at line four. The ANFIS is not good for this case, because it is much different from the proposed scenario, as shown on Fig. 7, so this line should be removed. In addition, we can remove the first line, because simulation time was two times longer than the rest of cases (see Table I). This result is interesting since it shows that the fuzzy approach should only be used for durations smaller or equal to the training. After that time, the error could be worse than the noncorrected system, and a parametric reset should be performed. With these considerations, the new values for averages and standard deviations are: $m_1 = 2.325\%$, $\sigma_1 = 0.52\%$, $m_2 = 0.718\%$ and $\sigma_2 = 0.58\%$. Now, the two standard deviations have close values and these are close to the value of standard deviation of the sensors noise. The average of the errors is still different, showing a better accuracy for the system with fuzzy corrections. The results are even more impressive if we analyze the error propagation in dead reckoning type navigation systems, in which errors increase with time. Further analysis shows three times better relative accuracy.

The positions of vehicle, actual, reported by INS alone and reported by INS after fuzzy corrections, in the case of 2-rules ANFIS, are presented in Fig. 8.

The same simulation was done, as for 2-rules ANFIS, for 3, 4, 5, 6, and 7-rules ANFIS. We put the averages and standard deviations for these situations in the Table II.

A system with three rules is optimal from the point of view of accuracy and used storage space. The average of the errors in the case of INS corrected by the ANFIS is 0.32%, which is seven times smaller than the average of the errors of stand-alone INS. This

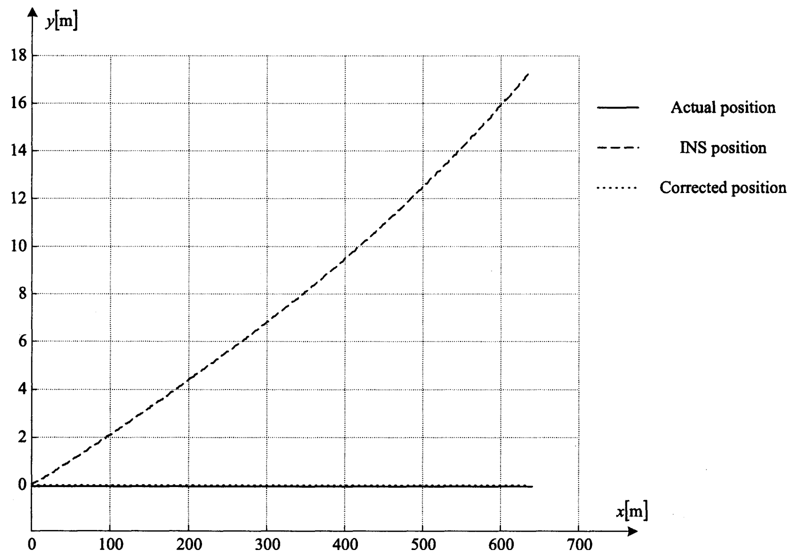


Fig. 8. Trajectories: actual, reported by INS, reported by corrected INS, for case 2 from Table I.

TABLE II
Influence of Number of Rules on Accuracy of System

No. of Rules	m_1 [%]	σ_1 [%]	m_2 [%]	σ_2 [%]	x Memory [B]	y Memory [B]
2	2.325	0.52	0.718	0.58	947	750
3	2.3525	0.56	0.32	0.255	1661	1102
4	2.44	0.39	0.34	0.285	2335	1567
5	2.37	0.451	0.343	0.286	3509	2128
6	2.5225	0.391	0.404	0.185	4751	2805
7	2.8025	0.0805	0.3375	0.2323	6213	3551

also means that the trained ANFIS can perform its task for 2.7 times longer than the stand-alone INS.

V. CONCLUSION

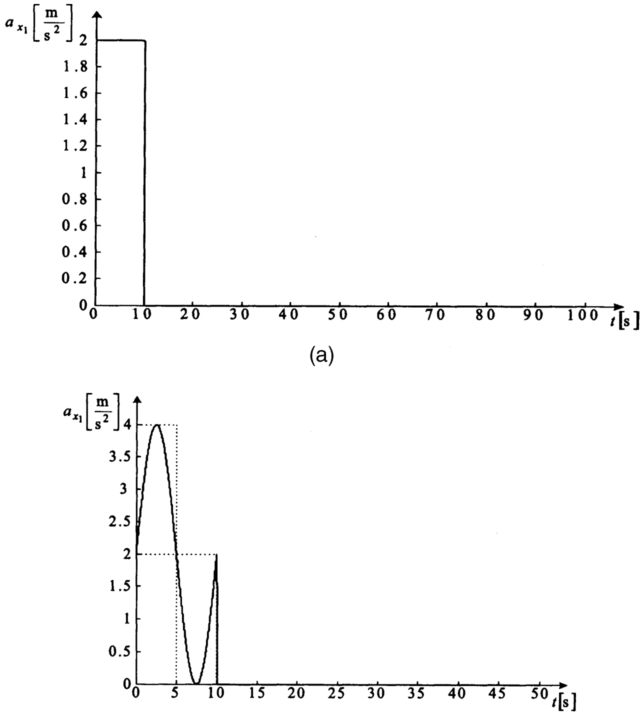
The principle of this algorithm is similar to the map recognition algorithm, since structured knowledge is used, in both cases, as a map or trained knowledge. Although the two algorithms are based on structured knowledge, the storage of a map in memory takes a lot of space and can only be used in a limited area. The required space for storage of the structured knowledge of ANFIS is much smaller and the knowledge is based on the evolution of the vehicle in any environment.

The proposed algorithm is not exhaustive since it is applicable only for the considered scenario. However, we considered the scenario only as an example, the approaches for other scenarios being not different. The difference will appear only in the dynamic behavior detector, which has to be adapted to select the best scenario, or even a combination of scenarios through a weighted average of different activated ANFIS.

In the Table I, we can see the flexibility of the ANFIS with respect to the input signal. This means that it will not be necessary to have many ANFIS, for many input signals characteristics, because the fuzzy systems are tolerant to faults and uncertainty. We did not present here all the simulation results. However, another conclusion is that we can better estimate the speed of vehicle, as magnitude and direction. It also helps to better manage the errors in the next stage of motion evaluation, which necessitates initial conditions to integrate the measurements.

In Fig. 10, we can see the variation of errors with respect to time, in the 3-rules ANFIS case, when a signal as in Fig. 9 is applied at the input. In Fig. 9, another acceleration of the vehicle is also shown that is used to test the system tolerance to uncertainty. We can appreciate the tolerance of the system to uncertainty comparing the two signals that are different, the second being a variation equal the full range of the first one.

If we admit a quadratic evolution of error, in the INS model, then the accuracy after fuzzy corrections is seven times better than without corrections (the exact value is 7.3), for the same duration of performing. If we put a threshold in accuracy, then the fuzzy system will perform three times longer than without corrections (the exact value is 2.7). If we want that the systems to provide the position within 100 m (C/A-code GPS accuracy), then the first system will perform for about 10 min and the second for



(a)

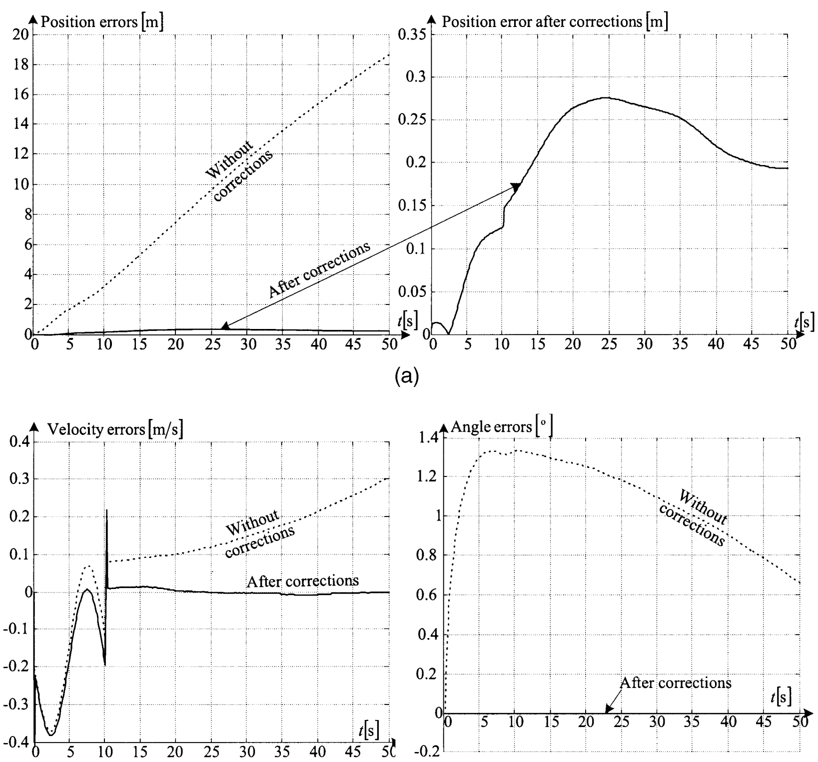
(b)

Fig. 9. Some signals used at input of navigation system. (a) Signal used to train ANFIS. (b) Signal applied to test tolerance at uncertainty.

30 min. If we put the threshold of accuracy at 10 m (the P-code GPS accuracy), then we estimate the performing time about 3 min and 9 min, respectively.

The approach presents the modality to build and train an ANFIS that can compensate part of the errors of a stand-alone INS, in the case when a disruption of GPS service occurs. The research shows that the goal is achievable in restrictive cases, for which the ANFIS was built and trained. This was the reason for taking into consideration the presence of the dynamic behavior detector in our schematics. We considered a restrictive trajectory with the intention to prove, in this early stage, the concept. A more developed dynamic behavior detector and an ANFIS which will take into consideration more scenarios are in the future research and development plans. The good news is that ANFIS for the proposed scenario has proved to be very flexible, doing its job when chosen scenario parameters vary up to 20%. The second good news is that all the information about ANFIS requires only a small amount of memory to be stored.

The use of training techniques in dynamic behavior detector and in fuzzy subsystem opens the possibility for the navigation system to recognize previously implemented scenarios and/or to adapt itself for new scenarios, making data acquisition from stand-alone INS and reference navigation system, building and training new ANFIS, performing with



(a)

(b)

(c)

Fig. 10. Errors of INS without corrections and after performing ANFIS corrections. (a) Absolute position error as reported by INS without and after ANFIS corrections. (b) Velocity error as reported by INS without and after ANFIS corrections. (c) Error of angle of velocity vector as reported by INS without and after ANFIS corrections.

better accuracy during the period that the reference system becomes unavailable. The adaptive process can be permanent, as long as the reference navigation system is available and has a good accuracy.

REFERENCES

[1] Vulnerability assessment of the transportation infrastructure relaying on the Global Positioning System (2001).
Final report prepared by John A. Volpe, National Transportation Systems Center for Office of the Assistant Secretary for Transportation Policy, U.S. Department of Transportation, Aug. 29, 2001.

[2] Weiss, J. D., and Shields, F. (1998)
GPS/INS integration in a severe urban environment.
IEEE Position Location and Navigation Symposium, Apr. 20–23, 1998, 432–440.

[3] Forssell, B. (1991)
Radionavigation systems.
London: Prentice-Hall, 1991.

[4] Lawrence, A. (1993)
Modern Inertial Technology. Navigation, Guidance and Control.
New York: Springer Verlag, 1993.

[5] Savage, P. G. (1998)
Strapdown inertial navigation integration algorithm design Part 1: Attitude algorithms.
AIAA Journal of Guidance, Control, and Dynamics, **21**, 1 (Jan.–Feb. 1998), 19–27.

[6] Savage, P. G. (1998)
Strapdown inertial navigation integration algorithm design Part 2: Velocity and position algorithms.
AIAA Journal of Guidance, Control, and Dynamics, **21**, 2 (Mar.–Apr. 1998), 208–221.

[7] http://www.nsd.es.northropgrumman.com/Navigation/#

[8] Military critical technologies. Part III: Developing critical technologies. Section 16: Positioning, navigation, and time technology.
Report prepared for Department of Defense by Defense Threat Reduction Agency, Dulles, VA, Oct. 1999 (updated May 2000).

[9] Bennett, S. M., Allen, D. E., Acker, W., and Kidwell, R. (2002)
Blended GPS/DR position determination system.
Report for KVH Industries, Inc., 2002.

[10] Karatsinides, S. P. (1994)
Enhancing filter robustness in cascaded GPS-INS integrations.
IEEE Transactions on Aerospace and Electronic Systems, **30**, 4 (Oct. 1994), 1001–1008.

[11] Carvalho, H., Del Moral, P., Monin, A., and Salut, G. (1997)
Optimal nonlinear filtering in GPS/INS integration.
IEEE Transactions on Aerospace and Electronic Systems, **33**, 3 (July 1997), 835–850.

[12] Crocetto, N., and Ponte, S. (2002)
Blunder detection and estimation with fuzzy logic: Applications to GPS code- and carrier-phase measurements.
In *9th Saint Petersburg International Conference on Integrated Navigation Systems*, Saint Petersburg, Russia, May 27–29, 2002, 95–104.

[13] Swanson, S. R. (1998)
A fuzzy navigational state estimator for GPS/INS integration.
In *IEEE Position Location and Navigation Symposium*, April 20–23, 1998, 541–548.

[14] Leach, B. W., Rahbari, R., and Dillon, J. (2002)
Low cost strapdown IMU/DGPS integrated navigator with fuzzy logic adaptive tuning.
In *9th Saint Petersburg International Conference on Integrated Navigation Systems*, Saint Petersburg, Russia, May 27–29, 2002, 264–273.

[15] Eck, C., Geering, H. L., and Bose, S. C. (2000)
Model based INS/GPS navigation. In *Proceedings of the 7th Saint-Petersburg International Conference on Integrated Navigation System*, Saint Petersburg, Russia, May 29–31, 2000, 95–102.

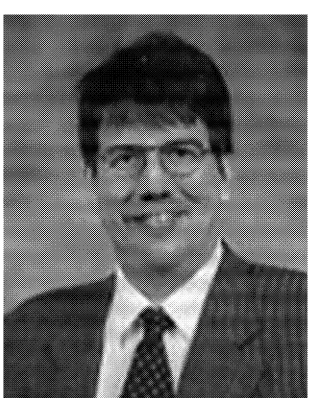
[16] Jang, J-S.R., and Sun, C-T. (1995)
Neuro-fuzzy modeling and control.
Proceedings of the IEEE, **83**, 3 (Mar. 1995), 378–406.

Adrian Hiliuta was born in Galati, Romania. He received the B.Eng. (1990) and Ph.D. (2001) degrees in aerospace engineering from the Military Technical Academy, Bucharest, Romania.

He was with the Romanian army, involved in flight testing for airplanes after major reparations. He was also a professor with the University of Craiova, Romania. In 2002 he worked as researcher in employing artificial intelligence to integrate different navigation systems. Since 2003 he is involved in projects regarding active aeroelastic wing developed by École de Technologie Supérieure (ETS), Montréal, Canada with NASA Dryden Flight Research Center, and in the project development of a global model parameter with smart sensors, carried out by ETS with Bell Helicopter Textron under CRIAQ program. His research interests cover navigation systems and the integration techniques between complex systems, aeroservoelasticity, parameter estimation, digital signal processing, smart sensors, and smart architectures using MEMS.

René Jr. Landry was born in Montreal in 1968. He received a B.E. degree at the Ecole Polytechnique of Montreal, Canada in 1992, a M.S. in satellite communication engineering at the University of Surrey, Guildford, England in 1993, a master in space electronics and a DEA in microwaves at the ENSAE/SupAero, Toulouse, France in 1994. He obtained his Ph.D. degree at Université Paul-Sabatier, Toulouse, France in 1997. He also received a Post Doc in Space Science at the National French Space Industry (CNES), Toulouse, France, in 1998.

Since 1999, he has been involved in the problem of GPS/Galileo/Bluetooth Interferences for the Canadian navigation and communication industries. His major interest concerns the development of new innovative mitigation techniques for GPS receiver robustness design including those of electronic inertial navigation system based on low cost MEMs. He is actually working on several digital signal processing applications in satellite navigation, anti-jamming and inertial navigation system.



François Gagnon (S'87—M'87—SM'99) was born in Québec City, PQ, Canada. He received the B.Eng. and Ph.D. degrees in electrical engineering from École Polytechnique de Montréal, Montréal, PQ, Canada.

Since 1991, he has been a professor in the Department of Electrical Engineering, École de Technologie Supérieure, Montréal, Canada. He chaired the department from 1999 to 2001 and is now the holder of the Ultra Electronics (TCS) Chair in wireless communication at the same university. His research interest covers wireless high speed communications, modulation, coding, high speed DSP implementations, and military point to point communications. He has been very involved in the creation of the new generation of high capacity line of sight military radios offered by the Canadian Marconi Corporation, which is now Ultra Electronics Tactical Communication Systems.