

Optimized Data Fusion in an Intelligent Integrated GPS/INS System Using Genetic Algorithm

Ali Asadian, Behzad Moshiri, Ali Khaki Sedigh and Caro Lucas

Abstract—Most integrated inertial navigation systems (INS) and global positioning systems (GPS) have been implemented using the Kalman filtering technique with its drawbacks related to the need for predefined INS error model and observability of at least four satellites. Most recently, a method using a hybrid-adaptive network based fuzzy inference system (ANFIS) has been proposed which is trained during the availability of GPS signal to map the error between the GPS and the INS. Then it will be used to predict the error of the INS position components during GPS signal blockage. This paper introduces a genetic optimization algorithm that is used to update the ANFIS parameters with respect to the INS/GPS error function used as the objective function to be minimized. The results demonstrate the advantages of the genetically optimized ANFIS for INS/GPS integration in comparison with conventional ANFIS specially in the cases of satellites' outages. Coping with this problem plays an important role in assessment of the fusion approach in land navigation.

Keywords—Adaptive Network based Fuzzy Inference System (ANFIS), Genetic optimization, Global Positioning System (GPS), Inertial Navigation System (INS).

I. INTRODUCTION

EVER since the artificial intelligence, considered as a powerful and applicable tool in engineering modeling, computation, nonlinear function approximation, system identification and estimation theory. The neurofuzzy models have the connectionist structure of neural networks combined with flexibility and intuitive learning capabilities of fuzzy systems. A variety of inference engines and learning algorithms have been discussed in the literature [1].

ANFIS (adaptive network based fuzzy inference system) is one of the most popular algorithms that has been used for different purposes such as system identification, signal processing, pattern recognition, control of dynamical systems and prediction. It has a hybrid learning method based on gradient descent and least square estimation [3]. Another new method which can be categorized in the intelligent approaches

is genetic algorithms. GAs as function optimizers are global optimization techniques based on natural selection. This form of evolutionary algorithm evolves throughout generations improving the features of potential solutions by means of biologically inspired operations. GAs are presented as a tool to optimize a certain objective function. Several usages of GAs have been found in the literature [4]-[7]. Here we will focus on optimization of the ANFIS network with GAs in the field of navigation applications. It will be shown that the mentioned estimator filter has an excellent performance when encountering satellites' outage as a great benchmark in assessment of fusion approach.

II. OVERVIEW

It is well established that global positioning system (GPS) can provide position and velocity information of moving platforms with consistent accuracy throughout the surveying mission. The limitations of GPS are related to the loss of accuracy in the narrow-street environment, intentional disruption of the service, S/A noise, poor geometrical-dilution-of-precision (GDOP) coefficient and the multipath reflections. GPS-based navigation system requires at least four satellites, so a major drawback of GPS dependence navigation systems is that their accuracy degrades significantly with satellites' outages. Signal outage is more significant for land vehicle positioning in urban centers, which takes place when encountering highway overpasses or tunnels due to the obstructed signals. So it is suitable to integrate this type of navigation system with a different type of navigation system in order to reach 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 INS is based on measurements of inertia of the vehicle, linear accelerations, and angular velocities. INS measures the linear acceleration and angular rates of moving vehicles through its accelerometers and gyroscopes sensors. 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 INS accuracy degrades over time, due to the unbounded positioning errors caused by the uncompensated gyro and accelerometer errors affecting the INS measurements. INS provides high-accuracy three-dimensional positioning when the GPS positioning is poor or unavailable over short periods of time. In addition, it provides

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much higher update positioning rates compared with the output rate conventionally available from GPS [2]. Anyway in order to utilize the benefits of these two navigation sensors and gain the advantages of the data fusion, we fuse the data gathered by each and use integrated system. There are several integration schemes using a blending filter such as extended kalman filter to combine the GPS and INS data [11],[13]-[14]. Kalman filter as a classic approach provides poor prediction of position errors, when encountering satellites' outages. In order to reduce the impact of accuracy decreasing when GPS becomes unavailable an ANFIS has been used on a simplified 2-dimentional navigation model, built and trained using data from stand-alone INS on one hand, and from the GPS on the other hand [9]. For this purpose, the GPS-derived positions and velocities are excellent external measurements for updating the INS, thus improving its long-term accuracy. This fact has been illustrated in Fig. 1.

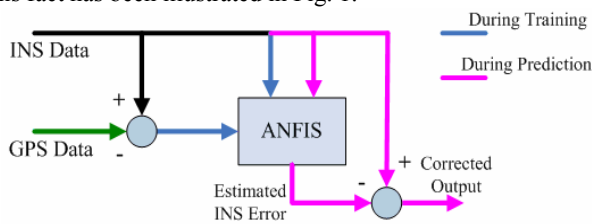


Figure 1 : Intelligent GPS/INS integration with ANFIS

The ANFIS can be built and trained during the availability time of reference system. So the data from GPS and 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 intelligent correction algorithm.

III. GENETIC ALGORITHM OPTIMIZATION

The GAs behave much like biological genetics [4]-[8]. The GAs are an attractive class of computational models that mimic natural evaluation to solve problems in a wide variety of domains. They introduce a population of individual solutions to an optimization problem and then evaluate the fitness of each individual in this population. Limited by the laws of natural selection, individuals with most suited elements in a population and better performance survive while those with weak performance are weeded out. The optimization process gets its dynamic by developing new generations of potential solutions and evaluating the degree of fitness of each generation and allowing it to proceed if it satisfies specific selection criterion which is usually based on a fitness-proportional selection. The process of developing new generations is also governed through the implementation of two operators: crossover and mutation.

GAs map a problem onto a set of strings or chromosomes, each string represents a potential solution. The three most important aspects of using GAs are:

- definition of the objective function
- definition and implementation of the genetic representation
- definition and implementation of the genetic operators

The speed of genetic algorithm depends heavily on the encoding scheme of the chromosomes and on the genetic operators that work on these chromosomes. The following is a pseudo code for a general GA:

- **Generate the initial parent population**
- **Evaluate** the initial parent population
- **Loop** until **termination** criteria is satisfied
 - **Select** chromosomes for reproduction
 - Create offspring using reproduction operators such as **crossover** and **mutation**
 - **Replace** parent population by offspring population
 - **Return fittest chromosome** of last parent population

IV. MATHEMATICAL MODEL OF INTEGRATED GPS/INS SYSTEM

Several mathematical models of different orders have been proposed in order to integrate INS and GPS sensors [11]-[13]. Here we use the model proposed in [13]. Note that measurements by accelerometers and gyros are expressed in the platform frame while the GPS measurements are given in an rectangular Earth Centered Earth Fixed (ECEF) frame. The geodetic coordinate system is defined according to the familiar latitude(λ), longitude(ϕ), and height(h) coordinate system so the Earth's geoid is approximated by an ellipsoid based on parameters given in Table I [14]. The relation between these two coordinate system is also given by (1-3).

TABLE I
PARAMETERS OF WGS84 REFERENCE FRAME

Symbol	Quantity	Value
A	semi major axis	6378.137 km
B	semi minor axis	6345.752 km
ω_e	earth's angular velocity	7.292115×10^{-5}
F	ellipsoid's flatness	3.352511×10^{-3}
e	ellipsoid's eccentricity	0.05781

$$R_\lambda = a(1 - e^2) / \sqrt{\{1 - e^2 \sin^2(\lambda)\}^3} \quad (1)$$

$$R_\phi = a / \sqrt{1 - e^2 \sin^2(\lambda)} \quad (2)$$

$$\begin{pmatrix} X_m \\ Y_m \\ Z_m \end{pmatrix} = \begin{pmatrix} (R_\phi + h) \cos(\lambda) \cos(\phi) \\ (R_\phi + h) \cos(\lambda) \sin(\phi) \\ (R_\phi(1 - e^2) + h) \sin(\lambda) \end{pmatrix} \quad (3)$$

For simplicity we assume that the gyros and the accelerometers are aligned with the axis in the platform frame. Also we assume that the body frame and the platform frame are aligned, and the center of the coordinate system is the same for both frames.

The transformation from body frame to local geographical frame is calculated at every moment and expressed as follow :

$$dR_{b2g} = R_{b2g} \Omega_{gb}^b dt \quad (4)$$

where :

$$\Omega_{gb}^b = \begin{pmatrix} 0 & -r & q \\ r & 0 & -p \\ -q & p & 0 \end{pmatrix} \quad (5)$$

$$\omega_{gb}^b = \begin{pmatrix} p \\ q \\ r \end{pmatrix} = \begin{pmatrix} \tilde{p} \\ \tilde{q} \\ \tilde{r} \end{pmatrix} + \begin{pmatrix} b_p \\ b_q \\ b_r \end{pmatrix} - R_{g2b} \begin{pmatrix} \omega_{ie} \cos(\lambda) + V_E / (R_\phi + h) \\ -V_N / (R_\lambda + h) \\ -\omega_{ie} \sin(\lambda) + V_E \tan(\lambda) / (R_\phi + h) \end{pmatrix} \quad (6)$$

ω_{gb}^b is the inertial angular rate expressed in the body frame where $(\tilde{p} \tilde{q} \tilde{r})^T$ is the measured angular rate and $(b_p b_q b_r)^T$ is the bias in the angular rate measurement. Finally the navigation-frame velocity in the local coordinate system is expressed according to :

$$\begin{pmatrix} V_N \\ V_E \\ V_D \end{pmatrix} = \begin{pmatrix} (R_\lambda + h) \dot{\lambda} \\ (R_\phi + h) \cos(\lambda) \dot{\phi} \\ \dot{h} \end{pmatrix} \quad (7)$$

The GPS receiver receives the signal corrupted by noise and other sources of error. If we could neglect the ionospheric and tropospheric errors, the observation equations or pseudoranges provided by i^{th} GPS satellite, have the following form :

$$\rho_i = \sqrt{(X_m - X_{si})^2 + (Y_m - Y_{si})^2 + (Z_m - Z_{si})^2} + c\delta \quad (8)$$

Where (X_m, Y_m, Z_m) and (X_{si}, Y_{si}, Z_{si}) are the coordinates of the receiver and the i^{th} satellite respectively. c is speed of the light and δ equals clock drift. In order to simplify the design process, it's assumed that the receiver coordinates in ECEF frame can be extracted from the pseudoranges through out the use of an external extended kalman prefilter.

The GPS clock drift and the INS equations constitute key dynamics in an integrated INS/GPS system (9-14) :

$$d \begin{pmatrix} V_N \\ V_E \\ V_D \end{pmatrix} = \begin{pmatrix} -V_E^2 \tan(\lambda) / (R_\phi + h) - 2\omega_{ie} \sin(\lambda) V_E + V_N V_D / (R_\lambda + h) \\ V_E V_N \tan(\lambda) / (R_\lambda + h) + \omega_{ie} \{ \sin(\lambda) V_N + 2 \cos(\lambda) V_D \} + V_E V_D / (R_\phi + h) \\ -V_N^2 / (R_\lambda + h) - 2\omega_{ie} \cos(\lambda) V_E - V_E^2 / (R_\phi + h) \end{pmatrix} dt + R_{b2g} \left\{ \begin{pmatrix} \tilde{a}_x \\ \tilde{a}_y \\ \tilde{a}_z \end{pmatrix} + \begin{pmatrix} b_a \\ b_b \\ b_c \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ g \end{pmatrix} \right\} dt + d\omega_i^x$$

$$d \begin{pmatrix} \lambda \\ \phi \\ h \end{pmatrix} = \begin{pmatrix} 1/(R_\lambda + h) & 0 & 0 \\ 0 & 1/[(R_\phi + h) \cos(\lambda)] & 0 \\ 0 & 0 & -1 \end{pmatrix} \begin{pmatrix} V_N \\ V_E \\ V_D \end{pmatrix} dt$$

$$d \begin{pmatrix} b_a \\ b_b \\ b_c \end{pmatrix} = -b_1 \begin{pmatrix} b_a \\ b_b \\ b_c \end{pmatrix} dt + d\omega_i^{p1}$$

$$d \begin{pmatrix} b_p \\ b_q \\ b_r \end{pmatrix} = -b_2 \begin{pmatrix} b_p \\ b_q \\ b_r \end{pmatrix} dt + d\omega_i^{p2}$$

$$dx_i = -ax_i dt + d\omega_i^x$$

$$d\delta = x_\delta dt$$

$$(9-14)$$

Where g is the gravitational acceleration, $(\tilde{a}_x \tilde{a}_y \tilde{a}_z)^T$ is the accelerometer measurement expressed in the body frame, $(b_a b_b b_c)^T$ is the accelerometer measurement bias again

expressed in the body frame. ω_i^x , ω_i^y , ω_i^z and ω_i^{p2} are vectors of brownian motion process with zero means and known covariance matrixes. The clock drift δ is represented by the integration of an exponentially correlated random process x_δ .

V. ARCHITECTURE OF PROPOSED NETWORK

In the previous studies [9]-[10], the ANFIS parameters (β as step size, β_i as step increase rate and β_D as step decrease rate) were tuned manually by trial and error to prove the efficiency of ANFIS. It has been shown that changing these parameters could significantly affect ANFIS prediction capabilities and have considerable effect in our application while changing the number of fuzzy rules is unlikely to produce any significant impact. Therefore, the tuning process should be automatized to allow system utilization in real-time applications. So it's proposed that a GA to be used to optimize ANFIS network parameters during the training mode with the objective of achieving the minimum training error. This new scheme has been illustrated in Fig. 2.

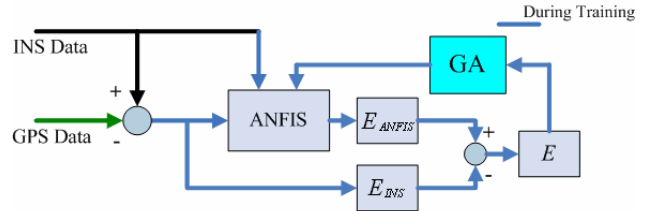


Figure 2: Intelligent GPS/INS integration with optimized ANFIS with GA

The proposed scheme will cause considerable reduction of position error than those reported before. 17 separate ANFIS networks were developed for the whole state vector components. All the networks have similar architecture but different parameters and during the training process the parameters could be separately tuned for each network.

In the training mode the network's inputs include INS outputs and time while its desired output is E_{INS} as described in equation (15) where P denotes the corresponding position.

$$E_{INS} = P_{GPS} - P_{INS} \quad (15)$$

The system concept is to train the network during the GPS availability periods and then to predict the INS error signal once the GPS outage occurs. After training process, the ANFIS will produce an INS error, which can be denoted as E_{ANFIS} . Then the modeling error is defined as (16) :

$$E = E_{INS} - E_{ANFIS} \quad (16)$$

By defining the root mean square of the modeling error for n observations as (17), then objective function for the GA is chosen to minimize the RMSE by optimizing ANFIS network parameters (β , β_i and β_D).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n E_i^2} \quad (17)$$

VI. SIMULATION RESULTS

The simulation was made with a relatively low IMU sample rate, 10 Hz in order to speed up the simulation. Pseudoranges are available with the rate of 1 Hz.

The kinematic data used were generated by Satnav toolbox created by GPSoft. In our test, the following profile as Fig. 3 containing one pitch manoeuvre in the beginning and one 90 degree turn in the middle of scenario was used.

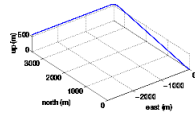


Figure 3: The flight scenario

The GA was implemented using the genetic optimization algorithm toolbox developed in MATLAB 7 package. The algorithm utilized a crossover rate of 0.75 and a probability of mutation of 0.001. 18 generations were created by the GA algorithm to search for the minimum RMSE. The change of the RMSE of the network versus the GA generation number is presented in Fig. 4 showing its maximum, average and the minimum respectively. It can be noted that the search converged successfully to the minimum RMSE after 18 generations. The optimal parameters that led to the minimum of RMSE are shown in Table II.

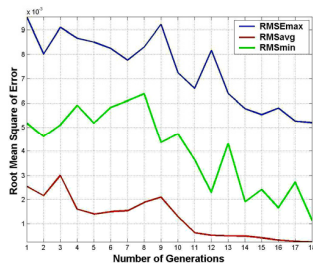


Figure 4: Change of RMSE versus the GA generation number

TABLE II
OPTIMAL PARAMETERS OF PROPOSED SCHEME

	Value
β	0.0298
β_I	1.6935
β_D	0.6221

After completion the training, then a complete GPS signal outage of 120 seconds starting at time 450 was intentionally introduced within the GPS data and both algorithms were used to predict the INS dynamic. The RMSE of the two networks during this period are compared in Table III.

TABLE III
POSITION RMSE OF THE NETWORKS DURING SATELLITES' OUTAGE

	RMSE(m)
ANFIS	2.684
Optimized ANFIS	1.123

It is obvious that the second network has a better performance than the alone ANFIS network as a result of genetic optimization. In the second case we need nearly 17.8% more computational effort but based on the results an improvement index of 58.2% in position estimation could be achieved. This fact could also be seen in Fig. 5. The left graph

relates to the ANFIS while the right one indicates the optimized ANFIS position error and its 3σ limit.

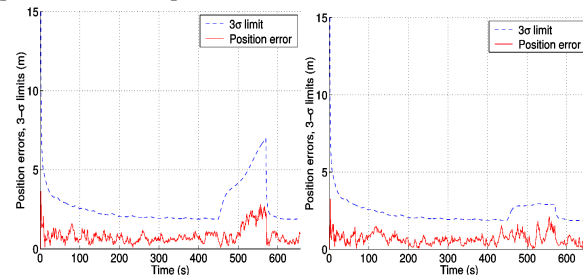


Figure 5: Comparison of position error of the two networks

VII. CONCLUSION

Genetic optimization applied to the adaptive neuro-fuzzy navigation system as a method to improve the estimation problem. Obtained results demonstrated the improved performance of this method over conventional ANFIS network. Although the proposed solution needs more computation effort but it showed outstanding performance in critical situations such as satellites' outages which is much likely in land navigation.

REFERENCES

- [1] D. J. C. MacKay, *Information theory, inference and learning algorithms*, U.K., Cambridge Univ. Press, 2003.
- [2] J. A. Farrel and M. Barth, *The global positioning system and inertial navigation*, New York: McGraw-Hill, 1999.
- [3] J. Shing and R. Shang, "ANFIS : adaptive-network-based fuzzy inference system," *IEEE Trans. Systems, Man and Cybernetics*, vol. 23, no. 3, pp. 665-685, May 1993.
- [4] P. D. Stroud, "Kalman-Extended genetic algorithm for search in nonstationary environments with noisy fitness evaluations," *IEEE Trans. Evolutionary Computation*, vol. 5, no. 1, pp. 66-77, February 2001.
- [5] T. Geisler and T.W. Manikas, "Autonomous robot navigation system using a novel value encoded genetic algorithm," In *Proc. 45th IEEE Int. Midwest Symp. on Circuits and Systems*, 2002, p. 45-48.
- [6] D. Loebis, R. Sutton and J. Chudley, "A fuzzy kalman filter optimized using a genetic algorithm for accurate navigation of an autonomous underwater vehicle," In *Proc. MCMC2003 Conf.*, September 17-19, Girona, Spain, pp. 19-24.
- [7] S. J. Simske, "Navigation using hybrid genetic programming : initial conditions and state transitions," HP intelligent enterprise Tech. Lab., Tech. Rep., Palo Alto, March 2003.
- [8] S. Luke and L. Spector, "A revised comparison of crossover and mutation in genetic programming," In *Proc. 3th Annu. Genetic Programming Conf. (GP98)*, San Francisco: Morgan Kaufmann, 1998, pp. 208-213.
- [9] A. Hiliuta, R. Jr. Landry and F. Gagnon, "Fuzzy correction in a GPS/INS hybrid navigation system," *IEEE Trans. Aerospace and Electronic Systems*, vol. 40, no. 2, pp. 591-600, April 2004.
- [10] J. H. Wang and Y. Gao, "Evaluating the accuracy of GPS positions under severe signal-degradation using adaptive-network-based fuzzy inference systems (ANFIS)," presented at the 50th CASI Annu. General meeting and Conf., Canadian Aeronautics and Space Inst., Montréal, Quebec, Canada, April 28 - 30, 2003.
- [11] D. Mc. N. Mayhew, "Multi-rate sensor fusion for GPS navigation using kalman filtering," M.S. thesis, Dept. Elect. Eng., Virginia Polytech. Inst. and State Univ., Virginia, USA, 1999.
- [12] X. He, Y. Chen and H.B.Iz, "A reduced-order model for integrated GPS/INS," *IEEE AES Systems Magazine*, pp. 40-45, MARCH 1998.
- [13] B. Azimi-Sadjadi, "Approximate nonlinear filtering with applications to navigation," Ph.D. dissertation, Dept. Elect. Eng., Maryland Univ., College Park, 2001.