GA BASED DATA FUSION APPROACH IN AN INTELLIGENT INTEGRATED GPS/INS SYSTEM

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

Abstract: A new concept regarding to the GPS/INS integration, based on artificial intelligence here is presented. 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, an INS/GPS integration method using a hybrid-adaptive network based fuzzy inference system (ANFIS) has been proposed in literature. During the availability of GPS signal, the ANFIS is trained 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. As ANFIS will be employed in real time applications, the change in the system parameters (e.g., the number of membership functions, the step size, and step increase and decrease rates) to achieve the minimum training error during each time period is automated. This paper introduces a genetic optimization algorithm that is used to update the ANFIS parameters with 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 when facing satellites' outages. Coping with this problem plays an important role in assessment of the fusion approach in land navigation.

1 INTRODUCTION

Ever since the artificial intelligence, has been considered as a powerful and applicable tool in engineering modeling, computation, nonlinear function approximation, system identification and estimation theory. The neuro-fuzzy 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 (Mackay, 2003). ANFIS 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 (Shing *et al.*, 1993). As discussed it has a hybrid learning method based on gradient descent and least square estimation. 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 (Goldberg, 1989 ; Michalewicz, 1996). This form of evolutionary algorithm evolves throughout generations improving the features of potential

Asadian A., Moshiri B., Khaki Sedigh A. and Lucas C. (2005).
GA BASED DATA FUSION APPROACH IN AN INTELLIGENT INTEGRATED GPS/INS SYSTEM.
In *Proceedings of the Second International Conference on Informatics in Control, Automation and Robotics*, pages 216-221
DOI: 10.5220/0001171802160221

solutions by means of biologically inspired operations. GAs are presented as a tool to optimize a certain objective function. For instance in GAs have been combined with extended kalman filter in order to increase the overall performance (Stroud, 2001). Several usages of GAs have been found in the literature (Geisler *et al.*, 2002 ; Loebis *et al.*, 2003 ; Simske, 2003). Here in this paper 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.

2 OVERVIEW

It's 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, 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. Besides the presence of noise in GPS signals, necessitates the use of narrow bandwidth filters which limits also the dynamic of the vehicle. 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 autonomy of INS is provided by the functioning principle, which is based on measurements of inertia of the vehicle, linear accelerations, and angular velocities. An 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. 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 (Farrel, 1999). 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.

Traditional integration which is accomplished by means of Kalman filtering has been shown in Figure 1. Where the INS outputs are compared to the outputs of the GPS. The errors in between are subjected to Kalman filtering, which enhances the performance of the navigation system by removing the effect of residual random errors during the surveying process (Mayhew, 1999).

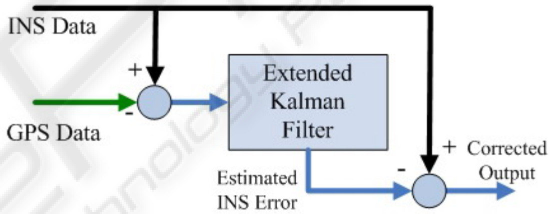

Figure 1: Traditional GPS/INS integration using Kalman filtering

As mentioned in the literature, Kalman filter provides poor prediction of position errors, when encountering satellites' outages. In order to prevent or, at least, to reduce the impact of accuracy decreasing when GPS becomes unavailable, an adaptive network based fuzzy inference system (ANFIS) has been used on a simplified 2-Dimensional navigation model, built and trained using data from stand-alone INS, on one hand, and from the GPS on the other hand (Hiliuata *et al.*, 2004). 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 Figure 2. The ANFIS could be built and trained during the availability time of reference system. Passing the INS data through ANFIS will procure a better accuracy when the reference source is missing. 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. A complete investigation has been performed to solve the navigation problem with real data via ANFIS network (Wang *et al.*, 2003).

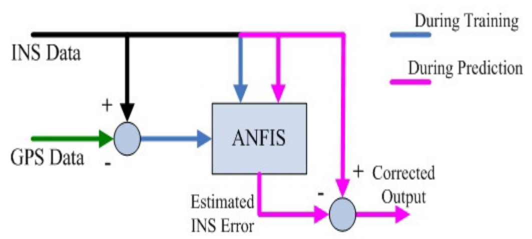

Figure 2: Intelligent GPS/INS integration with ANFIS

3 GENETIC ALGORITHM OPTIMIZATION

The GAs behave much like biological genetics and are an attractive class of computational models that mimic natural evaluation to solve problems in a wide variety of domains (Luke *et al.*, 1998). 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.

GAs map a problem onto a set of strings (the chromosomes), each string representing 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 (Geisler *et al.*, 2002).

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

4 MATHEMATICAL MODEL OF INTEGRATED GPS/INS SYSTEM

Several mathematical models have been proposed in order to integrate INS and GPS sensors (He, *et al.* , 1998). The number of states generally determines the accuracy of the modeling. Different models have been utilized in the literature. Here we use the model explained below (Azimi-Sadjadi, 2001).

Measurements of 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 longitude (λ), latitude(ϕ), and height(h) coordinate system. For this system of coordinates, the Earth's geoid is approximated by an ellipsoid. The defining parameters for the geoid according to the WGS84 reference frame are given in Table 1. and equations (1-2). The relation between these two coordinate system is also given by (3).

Table 1: Parameters of WGS84 reference frame

Parameter	Value
a (semi major axis)	6378.137 km
b (semi minor axis)	6345.752 km
ω_{ie} (earth's angular velocity)	7.292115×10^{-5} Rad/Sec
f (ellipsoid's flatness)	3.352511×10^{-3}
e (ellipsoid's eccentricity)	0.05781

$$R_\lambda = \frac{a(1-e^2)}{\sqrt{\{1-e^2\sin^2(\phi)\}^3}} \tag{1}$$

$$R_\phi = \frac{a}{\sqrt{1-e^2\sin^2(\phi)}} \tag{2}$$

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

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 as follows :

$$dR_{b2g} = R_{b2g}\Omega_{gb}^{b}dt \tag{4}$$

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

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

ω_{gb}^{b} is the inertial angular rate expressed in the body frame which can be expressed as follows in (6), where $(\tilde{p}\ \tilde{q}\ \tilde{r})^T$ is the measured angular rate, and $(b_q\ b_p\ b_r)^T$ is the bias in the angular rate measurement.

The GPS signal consists of a clock signal and a navigation message that are amplitude modulated. The GPS receiver receives the signal corrupted by noise and other sources of error. By neglecting the ionospheric and tropospheric errors which are highly correlated, the observation equations or pseudoranges provided by i^{th} GPS satellite, have the following form :

$$\rho_i = \sqrt{(X_{si} - X_m)^2 + (Y_{si} - Y_m)^2 + (Z_{si} - Z_m)^2} + c\delta \tag{7}$$

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.

Note that the above hypothesis is valid in most land navigation purposes. In order to simplify the design process in future, 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. We suppose this fact for the rest of this research so the outputs of the GPS sensor are supposed to be the receiver's coordinates. The GPS clock drift and the INS equations constitute key dynamics in an integrated INS/GPS system and could be expressed as (8-13) equations. where g is the gravitational acceleration, $(\tilde{a}_u\ \tilde{a}_v\ \tilde{a}_w)^T$ is the accelerometer measurement expressed in the body frame, $(b_u\ b_v\ b_w)^T$ is the accelerometer measurement bias again expressed in the body frame. w_t^v , w_t^x , $w_t^{b_1}$ and $w_t^{b_2}$ are vectors of brownian motion process with zero means and known covariance matrixes.

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

$$d\begin{pmatrix} V_N \\ V_E \\ V_D \end{pmatrix} = \begin{pmatrix} \dfrac{-V_E^2\tan(\phi)}{R_\lambda + h} - 2\omega_{ie}\sin(\phi)V_E + \dfrac{V_N V_D}{R_\phi + h} \\ \dfrac{V_E V_N\tan(\phi)}{R_\phi + h} + \omega_{ie}\{\sin(\phi)V_N + 2\cos(\phi)V_D\} + \dfrac{V_E V_D}{R_\lambda + h} \\ \dfrac{-V_N^2}{R_\phi + h} - 2\omega_{ie}\cos(\phi)V_E - \dfrac{V_E^2}{R_\lambda + h} \end{pmatrix}dt$$

$$+ R_{b2g}\left\{\begin{pmatrix} \tilde{a}_u \\ \tilde{a}_v \\ \tilde{a}_w \end{pmatrix} + \begin{pmatrix} b_u \\ b_v \\ b_w \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ g \end{pmatrix}\right\}dt + dw_t^v$$

$$d\begin{pmatrix} b_u \\ b_v \\ b_w \end{pmatrix} = -b_1\begin{pmatrix} b_u \\ b_v \\ b_w \end{pmatrix}dt + dw_t^{b_1}$$

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

$$dx_t = -ax_t dt + dw_t^x$$

$$d\delta = x_t dt \tag{8-13}$$

5 ARCHITECTURE OF THE PROPOSED NETWORK

In the previous studies 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 network for INS/GPS integration (Wang *et al.*, 2003). 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, these parameters' tuning process should be automatized to allow system utilization in real-time applications so it's suggested here that ANFIS network parameters shall be tuned automatically by means of genetic algorithms. 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 Figure 3. The proposed automatization process will cause considerable reduction of position error than those reported before.

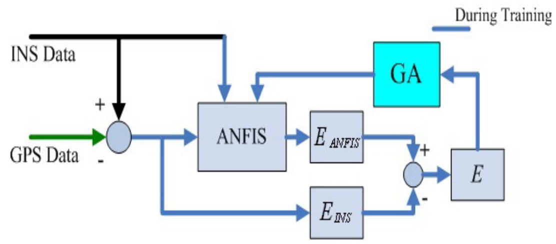

Figure 3: Intelligent GPS/INS integration with optimized ANFIS with GA

17 separate ANFIS networks were developed for integrating the INS/GPS for the whole state vector components. All the networks have similar architecture but different parameters. During the training process, the mentioned parameters can be tuned for each network separately to achieve the minimum training error for each time period and for each state vector component. In the training mode the network's inputs include INS outputs and time (T) while its desired output is E_{INS} as described in equation (14) where P denotes the corresponding position. 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.

$$E_{INS} = P_{GPS} - P_{INS} \tag{14}$$

After training process, the ANFIS network will produce an INS error, which can be denoted as E_{ANFIS} . Then the modeling error is defined as (15) :

$$E = E_{INS} - E_{ANFIS} \tag{15}$$

Then by defining the root mean square of the model error for n observations as (16) :

$$RMSE = \|E\|^2 \tag{16}$$

The objective function for the GA is chosen to minimize the RMSE by optimizing ANFIS network parameters.

6 SIMULATION RESULTS

The simulation was made with a relatively low IMU sample rate, 10 Hz. The GPS pseudoranges are available with the rate of 1 Hz. The kinematic data used in this study was generated by Satnav toolbox created by GPSoft. In our test, the following flight profile was used. This flight path (Figure 4) contains one pitch manoeuver in the beginning and one 90 degree turn in the middle of scenario.

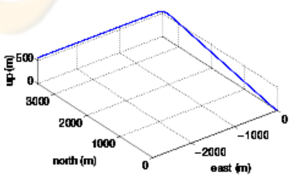

Figure 4: The flight scenario

The numerical parameters were selected as below. The last parameters model a typical quartz TCXO with frequency drift rate of $10^{-9}\ \mathrm{sec/sec}$.

$\sum_{w^{b_1}} = 4.905\times10^{-4} I$, $\sum_{w^{b_2}} = 0.09 I$, $\sum_{w^{v}} = 10^{-5} I$, $b_1 = b_2 = 0.0015$, $\sigma_{w^x} = 10^{-12}$, $a = 0.002$.

The GA was implemented using a genetic algorithm optimization toolbox developed in MATLAB 7 package. The algorithm utilized a crossover rate of ρ_c =0.75 and a probability of mutation of ρ_m =0.001. The proposed network was trained using the GA architecture described before. 18 generations were created by the GA algorithm to search for the minimum RMSE. The search converged successfully to the minimum RMSE after 18 generations. The ability of the two networks in correct prediction is compared in Figures 5 and 6. It's clear that the second network's output is a little bit better than the first one's.

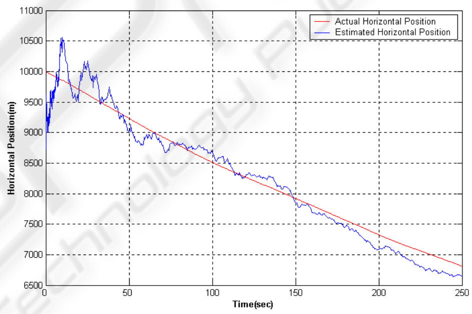

Figure 5 : Position tracking of the ANFIS

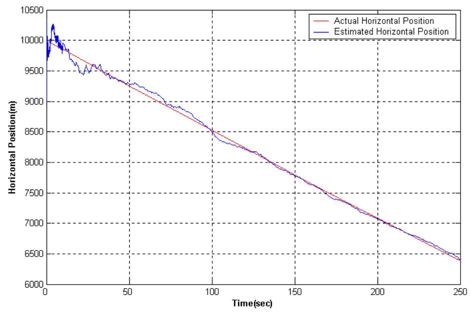

Figure 6: Position tracking of the optimized ANFIS

The optimal parameters that led to the minimum of RMSE are : β =0.0298, β_I =1.6935 and β_D =0.6221. After completion the training process, 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 during the outage period. In order to save computational effort, in this case GA optimization is only applied during satellites' outage. The RMSE of the two networks during this period were obtained as 2.684 for ANFIS and 1.123 for optimized ANFIS versus meters.

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 an improvement index of 58.2% in position estimation could be achieved. This fact could also be seen in the following figures :

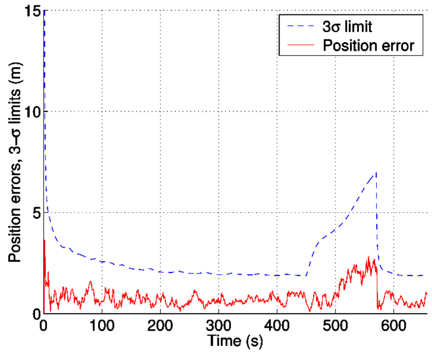

Figure 7: Position error of ANFIS network

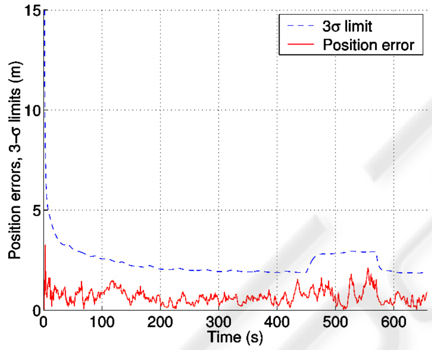

Figure 8: Position error of optimized ANFIS network

7 CONCLUSION

Genetic optimization applied to the adaptive neuro-fuzzy navigation system. It has been used as a method to improve the estimation problem . Obtained results demonstrated the improved performance of this method over conventional ANFIS network. Althought 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. To emphasize on the above advantage, the number of visible satellites intentionally degraded to zero during the simulation. The figures clearly prove the estimation improvement.

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