AUTOMIZATION OF AN INS/GPS INTEGRATED SYSTEM USING GENETIC OPTIMIZATION

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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, immunity to noise effects and observability. Most recently, an INS/GPS integration method using a hybrid-adaptive-neuro-fuzzy integration system (ANFIS) has been proposed by the authors. The advantage of the ANFIS over other classical filtering algorithms is its ability to deal with noise in the input data in dynamic environments. During the availability of GPS signal, the ANFIS is trained to map the error between the GPS and the INS. The ANFIS will then be employed to predict the error of the INS position components during GPS signal blockage. As ANFIS will be used 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. Challenges encountered in the integration process are discussed and the proposed architecture is tested in a land vehicle navigation. GPS signal outage of a time period of 120 seconds was simulated during 1420 seconds of land vehicle navigation. The experimental results demonstrated the advantages of the genetically optimized ANFIS for INS/GPS Integration.

KEYWORDS: Genetic Optimization; Global Positioning System (GPS); Inertial Navigation System (INS)

1. INTRODUCTION

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 [1]. However, as GPS-based navigation requires at least four satellites, a major drawback of GPS-dependence navigation systems is that their accuracy degrades significantly with poor satellite geometry, cycle slips, and satellite outages. Signal outage is more significant for land vehicle positioning in urban centers, which takes place when encountering highway overpasses or tunnels. On the other hand, an inertial navigation system (INS) measures the linear acceleration and angular rates of moving vehicles through its accelerometers and gyroscopes sensors, respectively. For short time intervals, the integration of acceleration and angular rate results in highly accurate velocity, position and attitude with almost no time lags. However, because INS position outputs are obtained by integration, they drift at low frequencies. To obtain very accurate outputs at all frequencies, the INS should be updated periodically using external measurements. For this purpose, INS measurements are integrated with GPS measurements to provide a navigation system that has superior performance in comparison with either a GPS or an INS stand-alone system. For instance, GPS-derived positions have approximately white noise characteristics over the whole frequency range. The GPS-derived positions and velocities are therefore excellent external measurements for updating the INS, thus improving its long-term accuracy. Similarly, INS can provide precise positioning data for GPS signal acquisition and reacquisition after outages. This reduces the time and the search domain required for detecting and correcting cycle slips [2]. Traditionally, this integration is accomplished by means of Kalman filter as shown in Figure 1. Where the INS outputs are compared to the outputs of the differential global positioning system (DGPS). 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 [3,4]. Kalman filter has been usually criticized for working under predefined models and for its observability problem of hidden state variables [5, 6]. It has been proved that the azimuth error state is a weakly observable component in Kalman filter [7]. Nassar et al. [8] showed that during GPS outages, Kalman filter provides poor prediction of position errors, thus deteriorating the overall accuracy of stand-alone INS

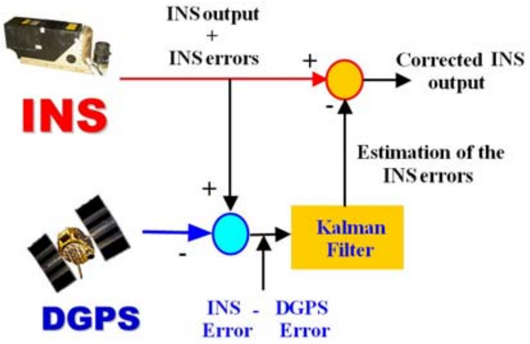


Figure 1. Typical INS/GPS integration system using Kalman Filter.

2. INS/GPS INTEGRATION USING FUZZY SYSTEMS

Most recently, Reda Taha et al. [9] proposed integrating the INS mechanization output and a DGPS output for land vehicle navigation by means of fuzzy systems. The system concept is that during GPS availability periods, the INS position error is defined as:

$$E_{INS} = P_{DGPS} - P_{INS} \tag{1}$$

where E_{INS} is the INS position error, and P_{INS} and P_{DGPS} are the INS and DGPS position outputs , respectively.

Adaptive neuro fuzzy inference systems (ANFIS) were chosen to perform the integration process as shown in Figure 2. In this scheme, the ANFIS system is trained during the GPS availability and then used to predict the INS error signal, E_{INS}, once the GPS outage occurs. Thus, the fuzzy system is used as a filter for INS/DGPS integration. Three separate ANFIS networks were developed for integrating the INS/GPS for the three position components: the height, the longitude and the latitude. The input parameters for ANFIS network included the mechanized INS stand-alone trajectory and the time period measured from the start of the period where the DGPS reading becomes available and its output is the INS error signal. While all the ANFIS networks have similar architecture, the number of membership functions, N_{mf}, for each network, the step size, and the rates of step decrease and increase during training of the system can be changed to provide optimized training. A pilot study by the authors [9] showed that changing these parameters is essential for providing optimal performance of the ANFIS filter during different GPS signal blockages. The step size, S, the step increase rate, α_I and step decrease rate,

α_D, are the parameters that regulate to what extent the training process can proceed in one direction during searching for the optimal solution [10]. During the training process, these parameters can be tuned for each network separately to achieve the minimum training error for each time period and for each positioning component.

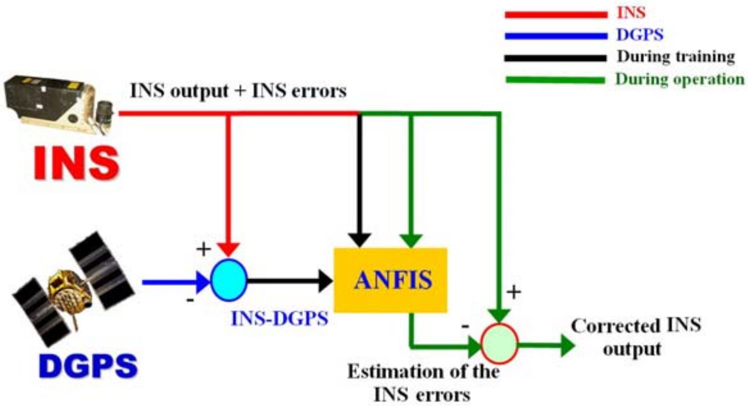


Figure 2. INS/GPS Integration using Fuzzy Systems

3. SYSTEM AUTOMIZATION USING GENETIC OPTIMIZATION

In the pilot study described above [9], the ANFIS network parameters (N_{mf}, S, α_I and α_D) were tuned manually to prove the efficiency of ANFIS network for INS/GPS integration. It was shown that these parameters could significantly affect ANFIS prediction capabilities. Therefore, the parameters' tuning process should be automized to allow system utilization in real-time applications. It is therefore suggested here that ANFIS network parameters shall be tuned automatically by means of genetic algorithms (GA). It is suggested that the GA will be used to optimize ANFIS network parameters during the training mode with the objective of achieving the minimum training error. The concept of genetically-controlled fuzzy and neural network systems is not new and has been discussed at different levels by Cordón et al. [11] and Ross [12] and has been implemented by other researchers in other fields [13]. The proposed automization process will allow reducing ANFIS training error considerably resulting in a better prediction and lower positioning errors than those reported before [9].

3.1. Genetic Algorithms

Genetic algorithms are numerical optimization approaches that are based on mimicking the natural selection theory. 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 better performance survive while those with weak performance are weeded out [14]. 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 by laws of natural selection through the implementation of two operators: crossover and mutation. Crossover allows best fit individual solutions to exchange some of their characteristics (e.g. part of their binary numbers) so that new generations will have the opportunity to have a better degree of fitness than their parents. As crossover cannot guarantee the introduction of new characteristics to individual solutions, the process of mutation is considered to ensure the diversity of the individual solutions (e.g. flipping binary 0 to 1 and vise versa). The mutation process occurs by forcing changes to the existing population and re-evaluating its fitness with these changes and is usually governed by a small probability of 0.001 or less [15]. The selection process is also constrained by the need to balance between exploration of the search space and exploitation of the discoveries made during the search process. This can be achieved by application of the Elitism rule, which requires the elite member to be selected and not to be disrupted by crossover or mutation [14].

3.2 Architecture of GANFIS Network

The root mean square error of the ANFIS network was chosen as the objective function to be minimized. In the training mode, ANFIS inputs include P_{INS} (INS position output) and time (T) while its desired output is E_{INS} as described in equation (1). When trained, the ANFIS network will produce an INS error, which can be denoted as E_{ANFIS} and the modeling error, E_{model}, is:

$$E_{model} = E_{INS} - E_{ANFIS} \qquad (2)$$

By defining the root mean square error of the model (RMSE) for n observations as:

$$RMSE = \sum_{i=1}^{n} E^2_{modeli} \qquad (3)$$

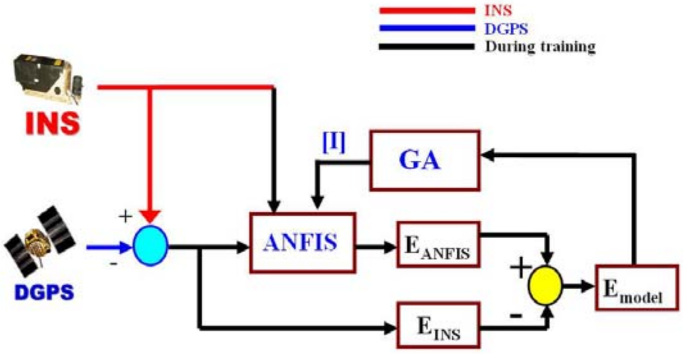


Figure 3. Architecture of GANFIS network for INS/GPS Integration

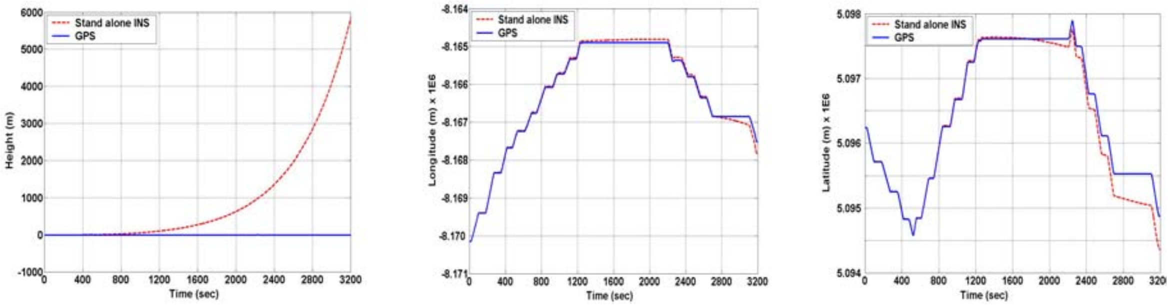
The objective function for the GA was to minimize the RMSE by optimizing ANFIS network parameters (N_{mf}, S, α_I and α_D). The pilot study [9] showed that changing N_{mf} is unlikely to produce any significant effect on ANFIS prediction abilities, while altering the step size and rates showed considerable effect. Thus, the optimization matrix "I" was limited to that in equation (4)

$$I = \begin{bmatrix} S & \alpha_I & \alpha_D \end{bmatrix} \qquad (4)$$

The genetically modified ANFIS system was named GANFIS. The architecture of the GANFIS network that was used to achieve the minimum RMSE during training is presented in Figure 3. The GA was implemented using a genetic algorithm optimization toolbox developed in MATLAB®. The algorithm utilized a crossover rate of 0.75 and a probability of mutation of 0.001. The elitism criterion was not implemented in this algorithm. The optimization problem was treated as a non-constrained, non-linear optimization problem.

4. EXPERIMENTAL DATA ANALYSIS AND DISCUSSION

The kinematic data used in this study was collected in Laval, Québec, Canada by the VISAT van mobile mapping system [9]. In this test, an Ashtech Z12 GPS receiver and a navigation-grade INS (Honeywell LRF-III) were used. The minimum number of available satellites was 7 and the average van speed was 50 km/h. A summary of the trajectory during 3200 seconds of testing time of the height, h, the longitude, λ, and the latitude, ϕ, is shown in Figure 4[a], [b] and [c], respectively. Due to space limitations, data regarding height only is discussed.



[a] [b] [c]

Figure 4. INS/DGPS measurements during 3200 seconds [a] height, [b] longitude, [c] latitude.

4.1. Network training using GA

The proposed ANFIS model was trained using the GA architecture described above. Twelve generations were created by the GA algorithm to search for the minimum RMSE. The change of the RMSE of the ANFIS network versus the GA generation number is presented in Figure 5 showing the maximum RMSE, the average RMSE and the minimum RMSE (RMSEmax, RMSEavg and RMSEmin), respectively. It can be noted that the search converged successfully to the minimum RMSE after 11 generations. The optimal parameters that achieved the minimum RMSE were 0.0438, 1.4252 and 0.7094 for S, α_I and α_D respectively.

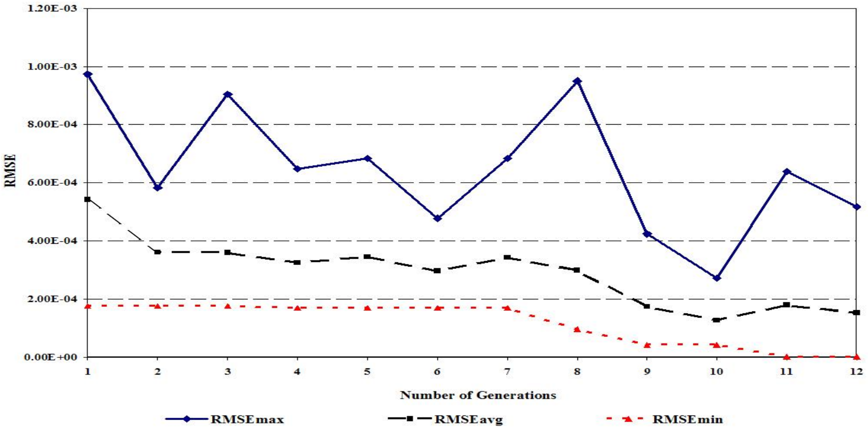


Figure 5. Change of RMSE versus the GA generation number.

4.2. INS/GPS integration using GANFIS

The genetically optimized ANFIS network (GANFIS) was tested against the original ANFIS model with S, α_I and α_D determined using trial and error. One GPS signal outage of 120 seconds time period starting at t_0 = 1401 was intentionally introduced within the GPS data and both algorithms were used to predict the INS position error during the outage period. The RMSE of GANFIS and ANFIS without GA optimization for the testing GPS outage period were compared. The RMSE for both systems during the simulated DGPS outage are presented in Table 1. It is obvious that the GANFIS network has a better performance than the ANFIS network as a result of genetic optimization. Further details of the GANFIS system are provided elsewhere [16].

Systems	ANFIS	GANFIS
RMSE	8.1914	3.351

Table 1: Model error during DGPS outage for both ANFIS and genetically optimized GANFIS

5. CONCLUSIONS

It is suggested here to use GA with ANFIS networks for providing automization for INS/GPS integration systems using ANFIS. Observing the INS and GPS trajectories during GPS availability provides ANFIS with the required learning data set to map the INS error based on GPS measurements. The GA is used during ANFIS training to minimize the RMSE of the ANFIS model, providing better performance and allowing real time applications. The proposed GANFIS system is tested in land vehicle navigation and has shown very promising results.

6. ACKNOWLEDGEMENTS

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