GPS/INS Integration Based on Dynamic ANFIS Network

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Abstract

This article presents a new structure for solving global positioning system (GPS) outages for long periods without requiring any prior information about the characteristics of the inertial navigation system (INS) and GPS. Kalman filter (KF) is widely used in INS and GPS integration to present a forceful navigation solution by overcoming the GPS outage problems. However, KF is usually criticized for working under predefined models and for its observability problem of hidden state variables, sensor dependency, and linearization dependency. Therefore, this article proposes a dynamic adaptive neuro-fuzzy inference system (DANFIS) to predict the INS error during GPS outages based on the current and previous raw INS data. The proposed integrated system is evaluated using a real field test data. The performance of the proposed technique is also compared with the traditional artificial intelligence (AI) technique and KF. The results showed great improvements in positioning and especially in velocity for MEMS grade IMU and for different length of GPS outages.

Keywords: *Global Positioning System (GPS), Inertial Navigation System (INS), Dynamic Adaptive Neuro-Fuzzy Inference System (DANFIS), Vehicular Navigation*

1. Introduction

Most of the modern vehicular navigation systems depend on the global positioning system (GPS) that is capable of providing a reliable position and velocity information. Unfortunately, GPS reliability requires a direct line of sight between the receiver and the satellite with minimum four satellites. This restriction may affect the accuracy of the system, since a GPS signal may be lost when moving around obstacles, in a canopy, between large building and tree lined streets [1].

On the other hand, navigation systems, in particular inertial navigation systems (INSs) have become important components in different military and civil applications. However, the INS accuracy degrades overtime due to the unbounded positioning errors caused by the uncompensated gyro and accelerometer errors affecting the INS measurements. Also it is well known that low-cost MEMS INS systems have much faster degradation than other types of inertial measurement unit (IMU) [2, 3]. Therefore, to obtain very accurate outputs at all frequencies, the INS should be updated periodically using external measurements. To achieve this goal, 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. GPS and INS both can be used for wide range of navigation functions. Each has its strength and weaknesses as illustrated in Table 1.

The GPS/INS integration is usually carried out through Kalman filtering (KF), which represents one of the best estimation techniques for augmenting signals from short-term high performance systems with reference systems exhibiting long-term stability. However, it still has many drawbacks. It requires a dynamic model for both INS and GPS errors, since it is usually difficult to set a certain stochastic model for each inertial sensor that works efficiently in all environments and reflects the long-term behaviour of sensor errors. In addition, there are several significant drawbacks such as sensor dependency, linearization dependency, and observability problems which are discussed in more detail in [5, 6].

Table 1: Comparison between INS and GPS Systems [4]

INS	GPS
Short term position and velocity accuracy	Long term position and velocity accuracy
Accurate attitude information	Noisy attitude information
Decreasing accuracy over time	Uniform accuracy over time
High measurement output	Low measurement output rate
Autonomous	Non-autonomous
No signal outages	Subject to signal outages
Affected by gravity	Not sensitive to gravity

Last decade has shown an increasing trend in using artificial intelligence (AI) to integrate the GPS with INS system. A variety of neural network methods have been introduced to integrate the GPS and INS [7]. In addition, [8] use dynamic neural network to increase the accuracy of prediction during GPS signal loss, however, neural network have some problems, such as their black-box nature, the lack of knowledge representation power, selection of the proper structure and size to perform the required real-time implementation [4, 9, 10].

Moreover, radial basis function (RBF) neural network was developed by [11] to fuse data from GPS and INS systems. The advantages of using RBF networks because it can overcome the problem of choosing the appropriate number of neurons in their hidden layer, as they are dynamically generated during the training phase to achieve the desired performance. But they didn’t consider the factors that affect the performance of the system during real-time implementation since it requires extended processing time and most important is that it required to perform the learning phase completely without any interruption since it generate the internal neurons during this phase and hence any interruption will cause failing to construct the INS error model required for correcting the INS output during the GPS signal loss.

In addition, hopfield neural network (HNN) was developed by [12] for estimating GPS/ INS error state and relaxes the assumptions made by the Kalman filter. However, it requires very large memory capacity since it is a recurrent neural network (RNN), thus it is time consuming for retrieving the stored learning parameters. Thus it can not be considered for real time implementation.

Adaptive neuro-fuzzy inference system (ANFIS) was applied for fusing GPS/INS data to work in real time [4, 7, 10, 13, 14]. The main objective of all previous integration techniques is to model the INS algorithm required to predict the instant INS error during GPS signal loss. All of the previous AI methods are utilized to model the INS error through relating the instant INS error to the instant INS data without taking into account the effect of past INS data. Moreover, the limitations of implementing ANFIS in real time are the difficulty of optimizing the INS error model depending on the instant INS data alone that may reduce the capabilities of real time implementation which results in poor navigation solutions during long GPS outages.

In this paper a novel dynamic ANFIS (DANFIS) model is presented through taking into account the trend of the previous INS data to be able to predict the instant INS error depending on the instant and previous INS data. Thus, it provides a reliable navigation solution during long GPS signal loss.

This paper is organized as follows: Section 2 describes the proposed dynamic adaptive neuro fuzzy inference system and its structure. Section 3 illustrates the methodology and the GPS/INS model architecture. The results obtained and discussion of the proposed dynamic intelligent navigator is given in Section 4. Finally, the conclusions from the results achieved are given in Section 5.

2. Dynamic Adaptive Neuro-fuzzy Inference System

Different interpretations for the fuzzy IF-THEN rules result in different mappings of the fuzzy inference engine while requiring a fuzzifier and defuzzifier to constitute a useful fuzzy logic system. Jang [15] proposed a neuro-fuzzy system utilizing the Sugeno FIS method through combining the explicit knowledge representation of FISs with the learning capabilities of the artificial neural network (ANN) in a complementary hybrid system called adaptive neuro-fuzzy inference system (ANFIS). This system is a universal approximator that is capable of uniformly approximating any complex and nonlinear function to any degree of accuracy utilizing a set of input and output data.

A dynamic ANFIS (DANFIS) is basically an ANFIS network that consists of multi-input-single-output (MISO). DANFIS can be utilized to build the conceptual intelligent GPS/INS navigator. In fact, it consists of two main parts: static ANFIS structure and memory elements. The memory can be represented by a shift register that have the ability to holds the previous INS position and velocity data samples.

The use of the shift register with the static ANFIS leads to the dynamic ANFIS as suggested by [16-19] since they use a static neural network with memory elements to produce the dynamic neural network (DNN) that can be used in different applications such as classification and identification. Therefore, the static ANFIS is transformed into the dynamic ANFIS since the shift register used at the ANFIS input presents a short-term memory. The number of neurons in the input layer for the ANFIS is equal to the number of the shift register elements. Figure 1 shows the dynamic ANFIS including the shift register used in this structure.

2.1 ANFIS Structure

The main advantage of using a hybrid intelligent system like ANFIS, over other classical filtering algorithms is its ability to deal with noise exists in the input data in dynamic environments. This intelligent system not only combine the learning capabilities of a neural network but also incorporate reasoning by using fuzzy inference by enhancing the capability of the system for prediction. The goal of ANFIS is to find a model or mapping correctly the inputs (raw input values) with their associated targets (predicted values) [4, 15].

The most useful class of defuzzifier is the center average of the form:

$$f(\underline{x}) = \frac{\sum_{j=1}^{M} y_j (\mu_{F_j}(y_j))}{\sum_{j=1}^{M} (\mu_{F_j}(y_j))} \tag{1}$$

Where M is the number of fuzzy IF-THEN rules, while y_j is the center of fuzzy set f_j, that is, a point in the universe of discourse V at which $\mu_{Fi}(y)$ achieves its highest value, and $\mu_{Fi}(y)$ is given by a product inference engine, since the product operator retains more information than MIN operator when implementing the fuzzy AND because the last scheme only preserve one piece of information whereas the product operator compose of n-pieces. Also, using product operator normally provides a smoother output surface, a desirable attribute in modeling and control systems.

Hence, equation (1) becomes:

$$f(\underline{x}) = \frac{\sum_{j=1}^{M} y_j (\prod_{i=1}^{n} \mu_{F_{ij}}(x_i))}{\sum_{j=1}^{M} (\prod_{i=1}^{n} \mu_{ij}(x_i))} \tag{2}$$

where n is the number of input linguistic variables.

In order to develop training algorithm for this fuzzy logic system, the functional form of $\mu_{Fi}(x_i)$ must be specified. The bell-shaped membership function, based on the normal distribution of the grades of the membership, would be used, since this function is differentiable and can be applied when using the back propagation learning algorithm, i.e. the membership function can be given by the following equation [20, 21]:

$$\mu_{F_i}(x_i) = \exp\left[-\left(\frac{x_i - m_i}{\sigma_i} \right)^2 \right] \tag{3}$$

where m_i and σ_i are, respectively, width and center of the bell shaped function of the i^{th} input variable.

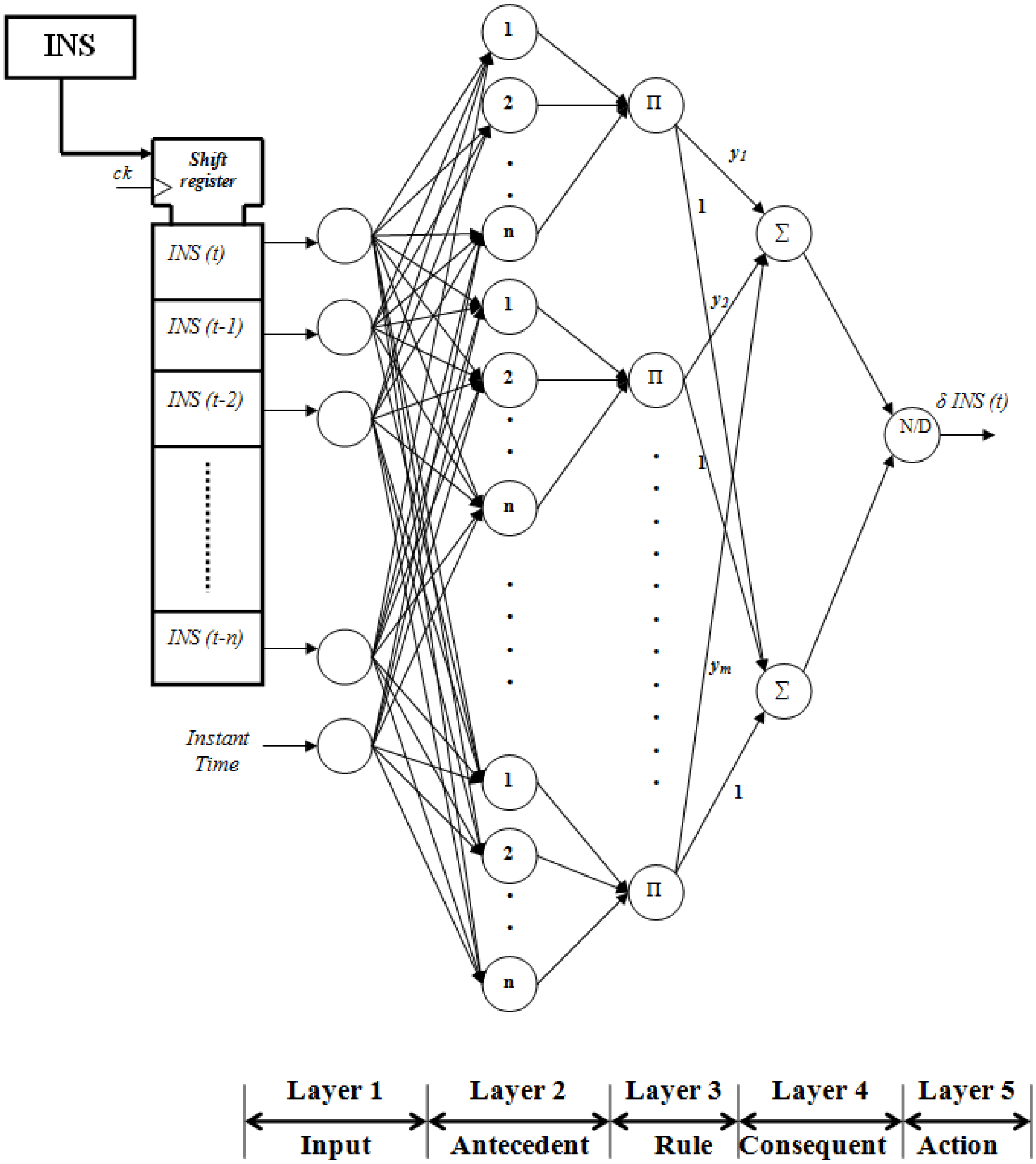


Figure 1. The Architecture of the Dynamic Adaptive Neuro Fuzzy Inference System Network

Now from equation (2) and equation (3) the overall function of fuzzy logic system can be obtained:

$$f(\underline{x}) = \frac{\sum_{j=1}^{M} y_j \left[\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - m_{ij}}{\sigma_{ij}} \right)^2 \right] \right]}{\sum_{j=1}^{M} \left[\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - m_{ij}}{\sigma_{ij}} \right)^2 \right] \right]} \tag{4}$$

This equation represents a fuzzy logic system with center average defuzzifier, product inference rule, singleton fuzzifier, and bell shaped membership function. Wang [22] shows that this fuzzy logic system is universal approximator (i.e. able of uniformly approximating any nonlinear function to any degree of accuracy).

Equation (4) can be embodying as a feed-forward neural network (NN) as exposed in Figure 1. This connectionist model adopted in Figure 1 mixes the approximate reasoning of fuzzy logic into a neural network structure.

With five-layered structure of the proposed connectionist model, the basic purposes of the nodes in each layer would be defined as below:

Associated with each node in a typical neural network is an integration function which serves to fuse information or activation from the other nodes.

This function X_i^1 provides the net input of the i^{th} node in layer l. A second action taken by each node is to output an activation value as a function of its net input:

$$O_i^1(k) = g(X_i^1(k)) \tag{5}$$

where $g(.)$ represents the activation function.

The functions of the nodes in each layer of the fuzzy-neural network can be summarized as follows [23]:

1) Input Layer

The unique function of these nodes in this layer is just transmits their input values directly to layer2:

$$X_1^1 = x_1 \ , X_2^1 = x_2 \ ,....., \ X_n^1 = x_n \tag{6}$$

$$O_i^1 = X_i^1 \tag{7}$$

where i=1,2,...,n and n is the number of the input linguistic variables.

2) Antecedent Layer

The output from this layer is described by:

$$O_i^2 = \mu_{F_i}(X_i^2) \tag{8}$$

where X_i^2 is the input to node i in layer2 and F_i is the linguistic label assigned to fuzzy set (small, large, etc.).

From equation (3), equation (8) becomes:

$$O_i^2 = \exp\left[-\left(\frac{X_i^2 - m_{ij}}{\sigma_{ij}}\right)^2\right] \tag{9}$$

where σ_{ij} and m_{ij} are the width and center of the bell-shape function of the i^{th} input of the j^{th} rule, respectively.

3) Rule Layer

The magnitude of the output from each node in this layer is dictated by the firing strength of a rule. With the proposed scheme (i.e. equation (4)), the rule nodes perform the fuzzy product operation; Therefore:

$$z_j = O_i^3 = \prod_{i=1}^{n} X_{ij}^{\ 3} \tag{10}$$

where X_{ij}^3 denotes the i^{th} input to node j in layer 3.

4) Consequent Layer

From this layer, the upper node sums all outputs from the rule layer with action strengths (y_j) and the lower node sums those with unity strength, as shown:

$$N = O_1^{\ 4} = \sum_{j=1}^{M} y_j X_j^{\ 4} \tag{11}$$

$$D = O_2^{\ 4} = \sum_{j=1}^{M} X_j^{\ 4} \tag{12}$$

where N and D represent, respectively, the numerator and denominator of equation (4).

5) Action Layer

Only one node exits in this layer. Here the actual output would be pumped out the net,

$$f(\underline{x}) = O^5 = \frac{N}{D} \tag{13}$$

2.2 Adaptive Fuzzy System Training Algorithm [10, 22]

Based on the idea of the error back propagation algorithm, the objective is to obtain a fuzzy logic system $f(x)$, in the form of equation (4), which minimizes the error function shown below:

$$E(k) = \frac{1}{2}\sum_{j=1}^{p}[\, f_j(x(k)) - d_j(k)]^2 \tag{14}$$

where P is the number of outputs and $d_j(k)$ is the j^{th} desired output (target) at time k. Without losing of generality, the multi input single output (MISO) fuzzy logic system was considered in this paper. A multi output system can always be decomposed into a set of single output systems, therefore for P=1, equation (14) is reduced to:

$$E(k) = \frac{1}{2}\big(f(x(k)) - d(k)\big)^2 \tag{15}$$

Referring to equation (4), if the number of rules in the proposed fuzzy system is M, then the difficulty becomes training the parameters y_j, m_{ij}, and σ_{ij} such that $E(k)$ is diminished. According to the back propagation training algorithm, the iterative equations for training the parameters y_j, m_{ij}, and σ_{ij} are:

$$y_j(k+1) = y_j(k) - \eta(f(\underline{x}(k)) - d(k))\frac{1}{D}O_j^{\ 3} \tag{16}$$

$$m_{ij}(k+1) = m_{ij}(k) - 2\eta\frac{Z_j}{D}(f(\underline{x}(k)) - d(k))\cdot(y_j(k) - f(\underline{x}(k)))\cdot\left(\frac{X_i^{\ 2}(k) - m_{ij}}{(\sigma_{ij})^2}\right) \tag{17}$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - 2\eta\frac{Z_j}{D}(f(\underline{x}(k)) - d(k))\cdot(y_j(k) - f(\underline{x}(k)))\cdot\left(\frac{(X_i^{\ 2}(k) - m_{ij})^2}{(\sigma_{ij})^3}\right) \tag{18}$$

where η is the learning rate. Equations (16), (17), and (18) perform an error back propagation procedure.

3. Methodology

The anticipated DANFIS for integrating INS with GPS systems establishes separate modules along the x, y, and z axes for position and along north, east, and down direction for velocity to predict the INS errors and to connect the GPS outages periods during GPS signal loss. Solving the GPS outage problems is the primary goal of integrating the GPS with INS. An additional goal of this paper is to solve this problem using a method suitable for real-time implementation. Therefore, the INS data will be divided into a number of frames. A certain length of 100 second is defined for each frame called a window. Therefore, the training phase will be conducted after gathering 100 samples of INS data instead of sample by sample. If the GPS signal loss is detected, the dynamic intelligent navigator will be switched to the prediction mode. This mode relies on the previously stored learning parameters to predict the INS error for the entire period of the frame, even though the period of signal loss is less than the defined window size. At the end of each frame, the dynamic intelligent navigator will evaluate the availability of the GPS signal before processing the next frame. The system will switch to the learning mode if the GPS signal is available.

3.1 DANFIS Architecture

Six separate DANFIS network is established to model both the position and velocity components in the three directions. The reliability of the proposed INS error models will be achieved through using hold out cross validation technique with a non-overlapping temporal window size of 100 second. During the updating mode as shown in Figure 2 the DANFIS networks for position and velocity components are trained using both the GPS and INS data to construct an empirical model related to the instant INS error for the instant and previous INS data samples for position and velocity respectively. The INS error (desired output) is computed during the GPS availability through subtracting the INS components from the corresponding GPS components for all position and velocity components. These data sets are then used to train six DANFIS networks corresponding to the six components of position and velocity. The inputs for each DANFIS network are the INS data (instant and previous samples) with the instantaneous time.

The intelligent dynamic navigator system, as shown in Figure 2 is trained to predict the INS error and provide accurate navigation solution for the moving vehicle. The DANFIS network output is compared to the desired INS error signal and the resulting difference is feedback to the network which adjusts its learning parameters in a way to minimize the mean square error value. The learning parameters for the DANFIS network that are calculated during the training phase are *m, y,* and *σ*. These parameters are updated according to equation (16), (17), and (18). The computations of these parameters are reiterated until the best possible values are realized (minimum mean square error) or the maximum iteration has been reached. Then the optimal values of learning parameters are saved to be used later during GPS outages. The preliminary values of the learning parameters (*m, y,* and *σ*) are initialized randomly the first time the intelligent dynamic navigator starts the training. Therefore, the user can specifies the number of epochs, the learning rate value, and the number of fuzzy rules (M). Table 2 shows the initial values for the parameters of DANFIS network which is obtained by trial-and-error. It must be mentioned that a precise selection of the learning parameters will ensures a good performance of the DANFIS networks that converge to a minimum error value.

During GPS signal loss the proposed DANFIS networks are then employed to process the instant and previous INS data to predict the instant INS position and velocity error as shown in Figure 3. Therefore, using previous INS data is anticipated to provide an accurate navigation solution during long GPS signal loss as will be shown in the experimental results.

In this paper, different numbers of input delay (i.e. memory elements) was considered in order to find the suitable number of input delay. Also, the outcome of using different number of input delay elements will be investigated and discussed in terms of time consumed and prediction accuracy through comparing the proposed DANFIS with the conventional ANFIS. The proposed DANFIS model performance is evaluated using real field test data collected from using MEMS IMU (Motion PakII) and NovAtel OEM4 GPS.

Table 2. Values of the Learning Parameters for the Six Networks

Initial Values	Position			Velocity		
	X-Axis	Y-Axis	Z-Axis	North	East	Down
m	[0, 8]	[-1,1]	[-3, 3]	[0,3]	[-2,2]	[0,2]
y	[0, 8]	[-1,1]	[-2,2]	[0,1]	[-1,1]	[0,2]
σ	[0.01, 1]	[0.01, 1]	[0.01,3]	[-2,2]	[-1,1]	[0,1]
M	10	10	10	10	10	10
Learning rate	0.3	0.3	0.3	0.3	0.3	0.3

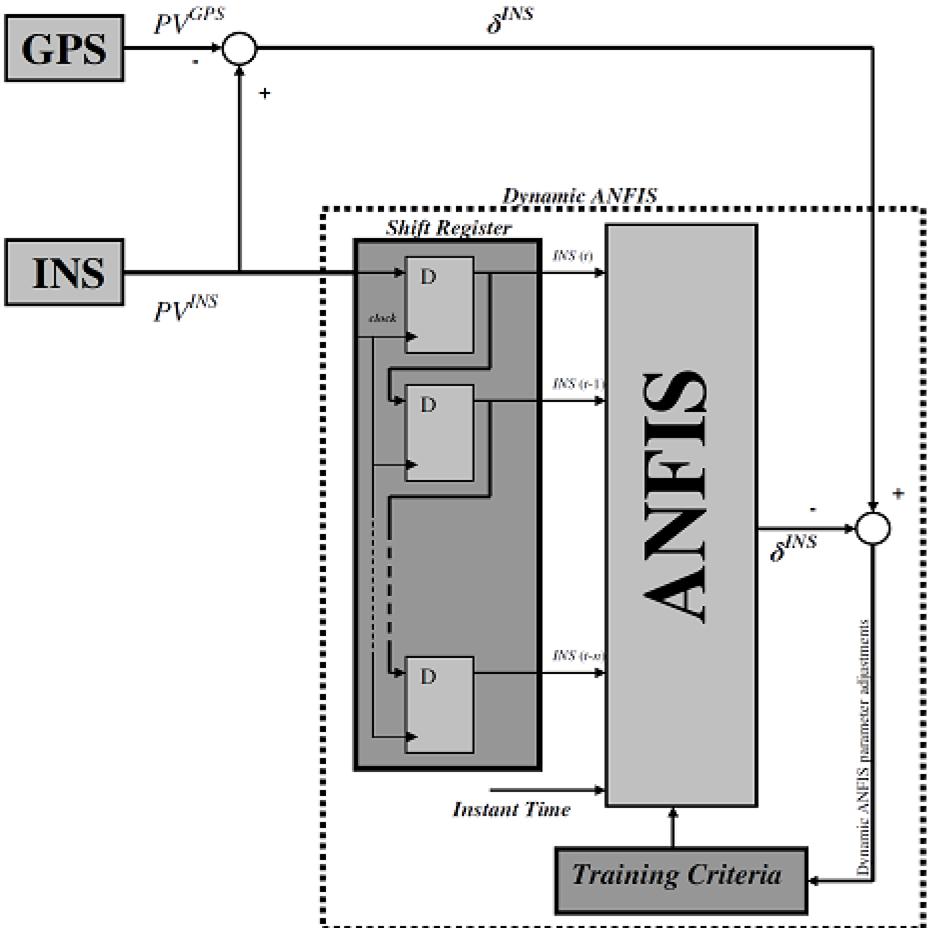


Figure 2. Dynamic ANFIS Scheme for GPS/INS Integration System during Updating Phase

4. Results and Discussion

To evaluate the effects of the dynamic ANFIS on predicting the INS error depending on both instant and previous INS data. A performance test is conducted for the dynamic ANFIS by taking into consideration the two modes of operation. The first mode is during the GPS availability though examining the DANFIS during updating mode when online learning on the INS error dynamics characteristics is conducted. In addition, the integrated system is also examined during GPS signal lost to validate the capability of the DANFIS model for accurate prediction of the INS position and velocity error patterns. In fact, the GPS are already available along the tested trajectories. Therefore, intentionally different outages were selected at different locations along the tested trajectory.

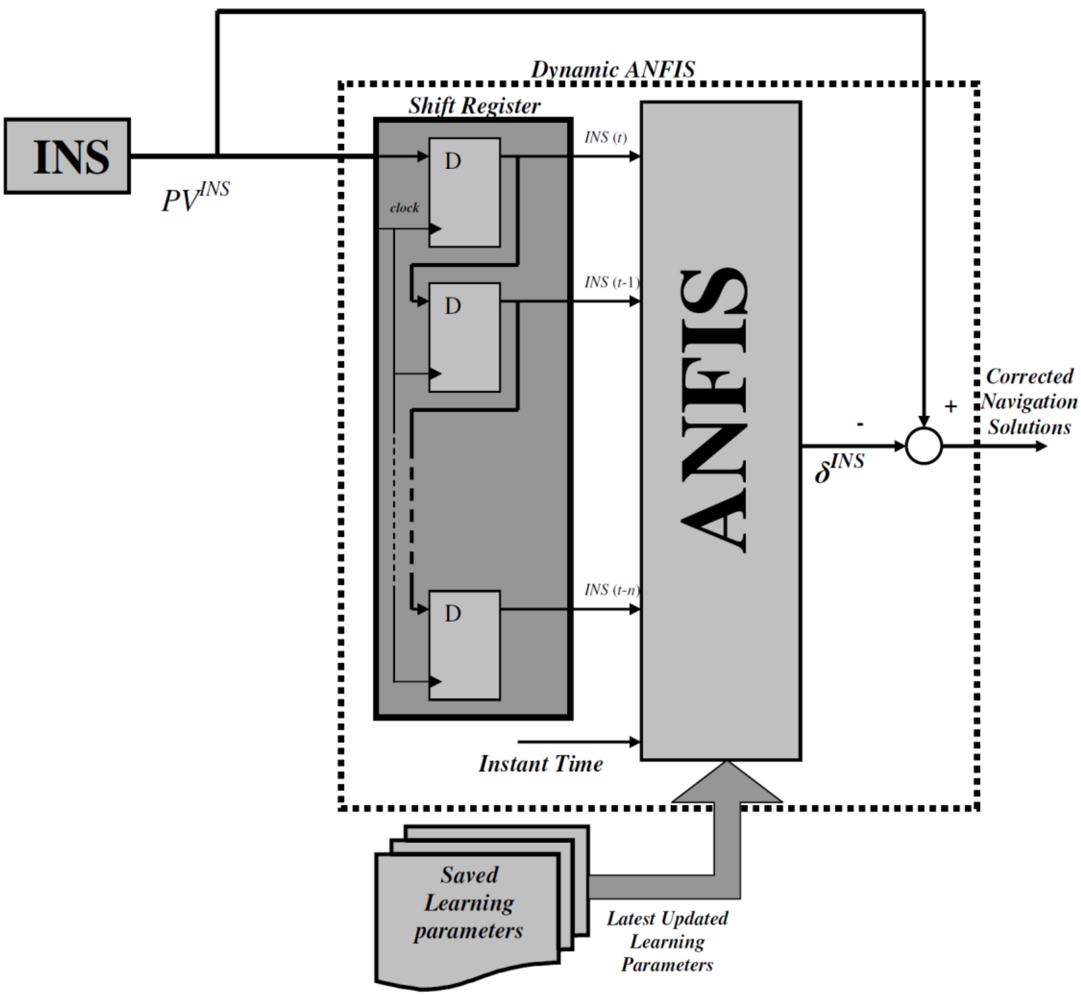


Figure 3. Dynamic ANFIS Scheme for GPS/INS Integration System during Evaluation Phase

The maximum position error obtained are less than 0.18, 0.24, 0.42, 0.67 and 1.18 m for (40, 50, 100, 150 and 200 second) outages respectively as shown in Figure 4 while a maximum error for velocity are less than 0.027, 0.03, 0.045, 0.048 and 0.05 m/sec for same outages periods as shown in Figure 5. Also, the difference between the desired and actual output of the DANFIS shown in Figure 6 indicate the superiority of the proposed DANFIS to provide the position and velocity components during GPS signal loss.

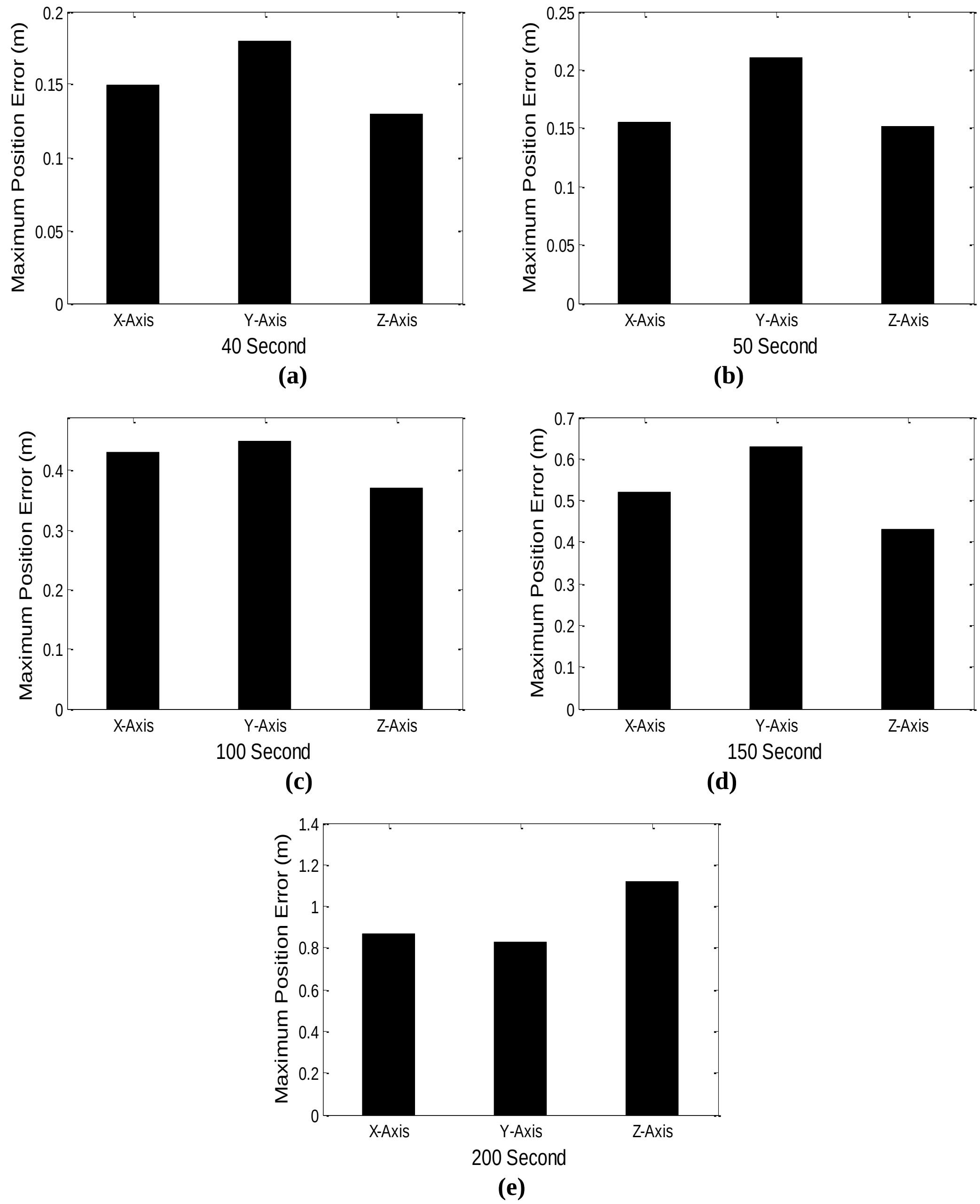


Figure 4. Maximum Position Error Results during Different GPS Outages (a) 40, (b) 50, (c) 100, (d) 150, and (e) 200 seconds

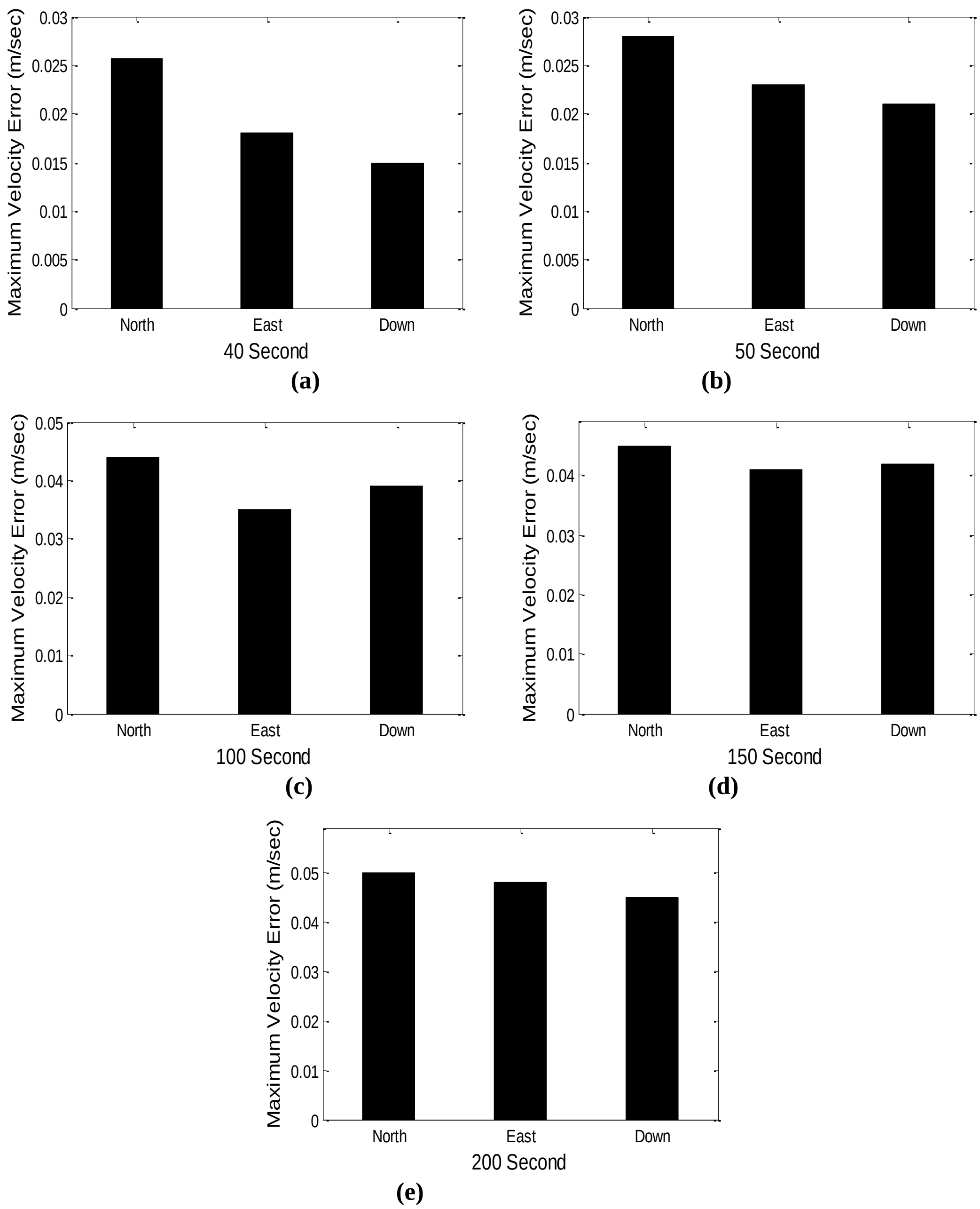


Figure 5. Maximum Velocity Error Results during Different GPS Outages (a) 40, (b) 50, (c) 100, (d) 150, and (e) 200 seconds

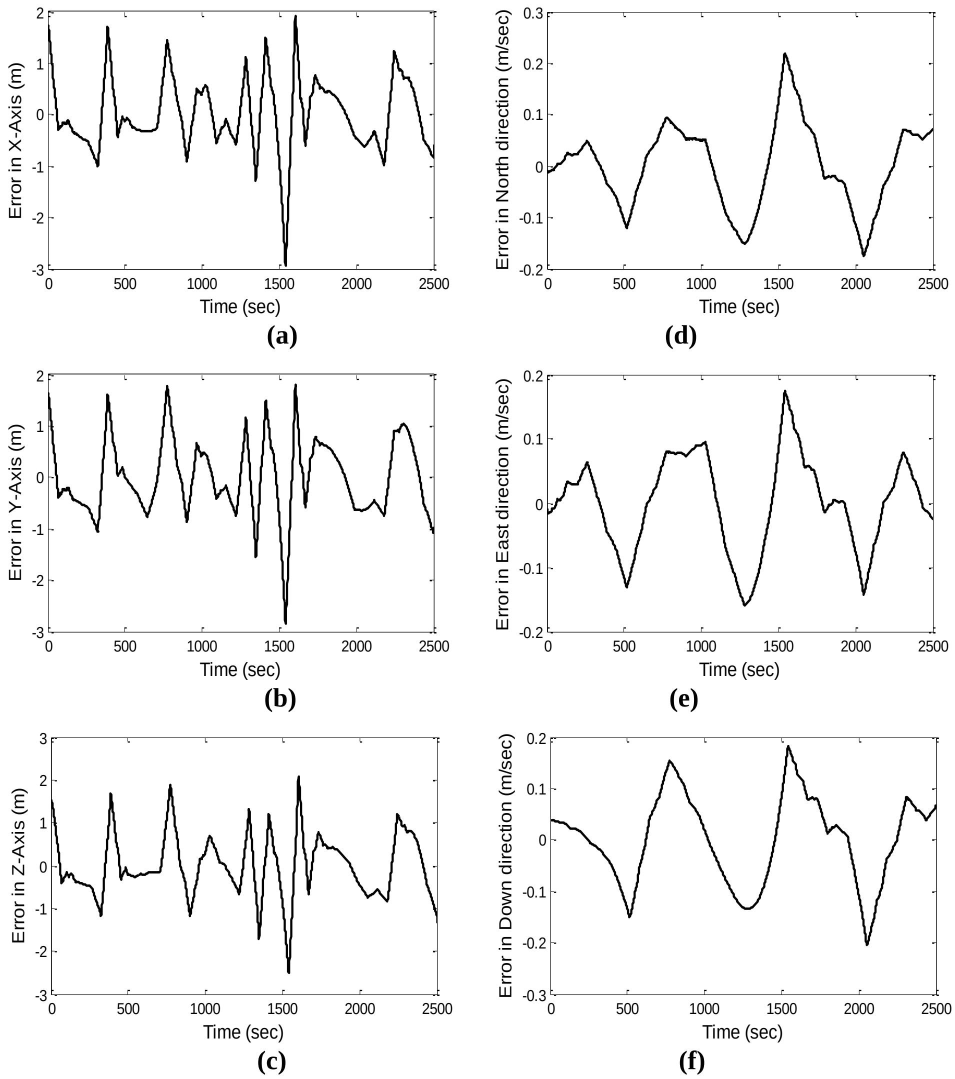
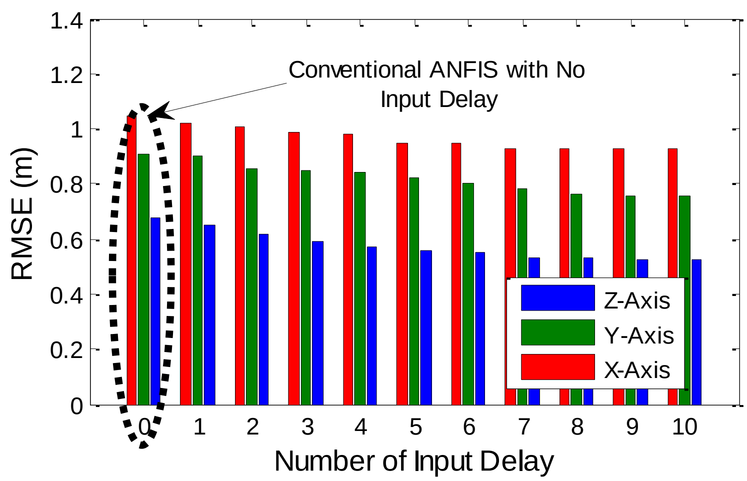
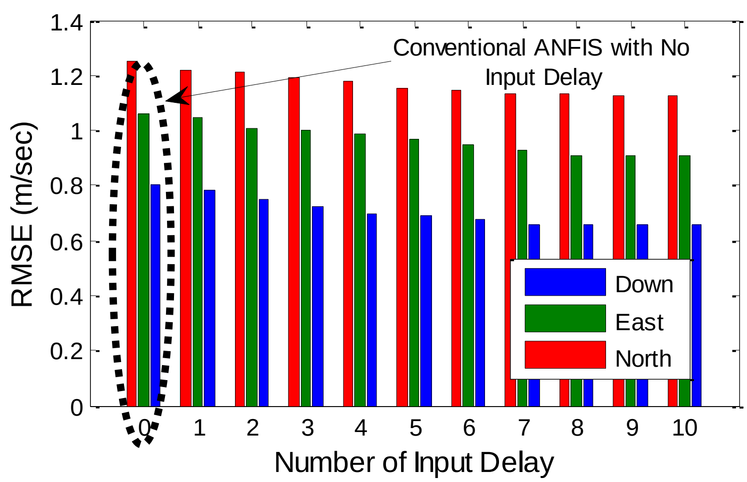


Figure 6. Error between the Desired and Actual Output of the Integrated GPS/INS Navigator Modules for Position in (a) X-Axis, (b) Y-Axis, and (c) Z-Axis, and Velocity in (d) North, (e) East, and (f) Down Directions.

The impact of using different number of input delay elements is a vital parameter to be investigated and study its effect in terms of reducing the prediction error and the time required for prediction. Therefore, Figure 7 shows that the root mean square error for both position and velocity is reduced as the number of input delay elements is increased. However, after reaching a certain number of input delays the reduction in the error value become invisible while the time increased dramatically as shown in Figure 8 which affects the condition required for real time implementation. Hence, increasing the number of input delay without limitation will increase the time required during training mode and increase the complexity of the proposed model since the number of membership functions will increased due to increasing the number of input delay as shown in Figure 9 which shows the relationship between the number of input delay and the number of membership functions required to keep the required root mean square error at a constant value. Finally, the results obtained using the proposed dynamic intelligent navigator is compared with the Kalman filter and it shows an elevated reduction in position and velocity errors as shown in Figure 10. Finally, Table 3 shows clearly that the proposed method improve the accuracy of the proposed intelligent navigator by 79%, 80%, 72% for position and 93%, 95%, 93% for velocity in the three directions compared to Kalman filter.

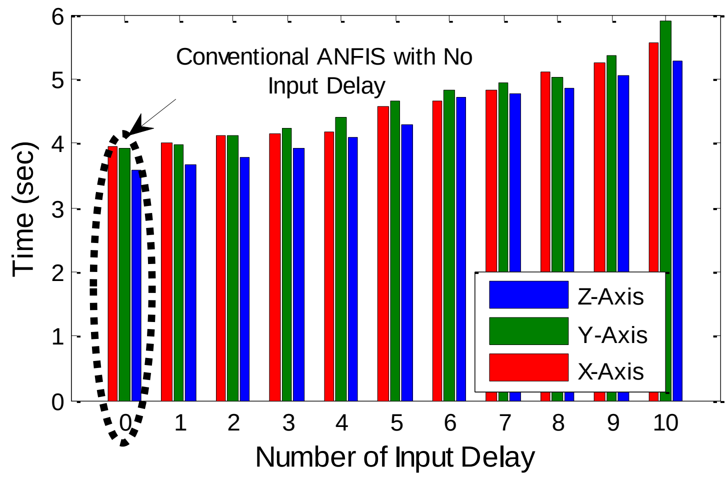


(a)

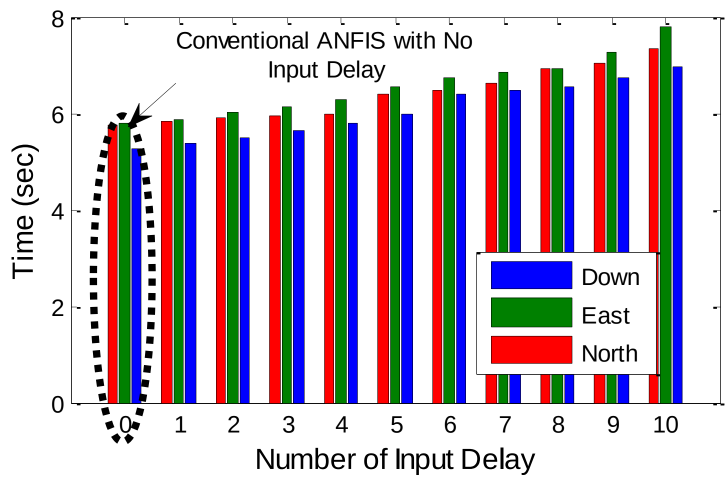


(b)

Figure 7. Impact of Increasing the Number of Input Delay Elements for (a) Position and (b) Velocity

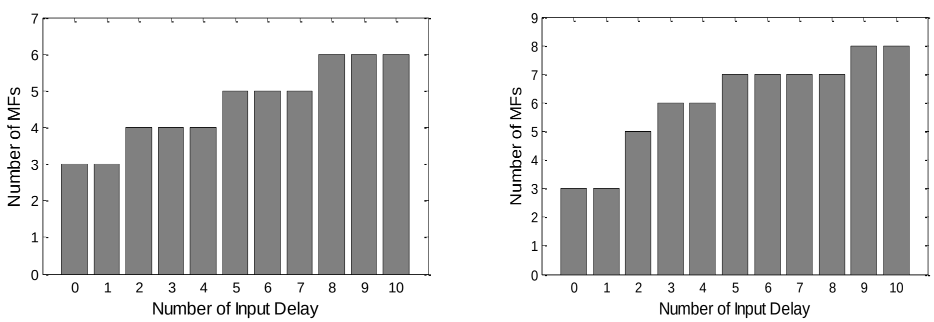


(a)



(b)

Figure 8. Average Time for 200 second by repeating each Experiment Five Times for all Components in (a) Position, and (b) Velocity



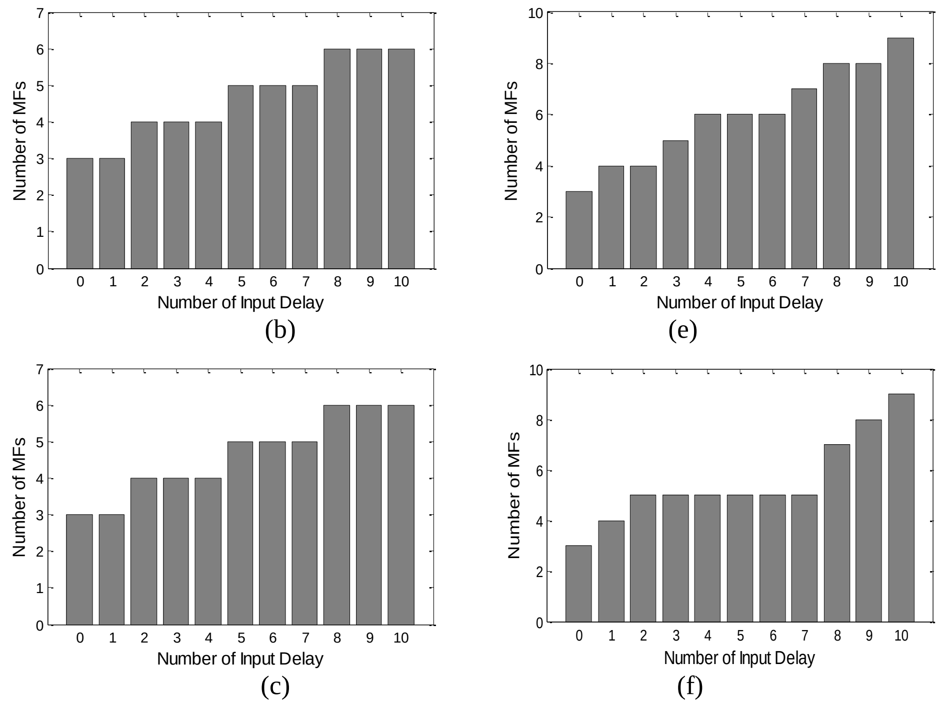
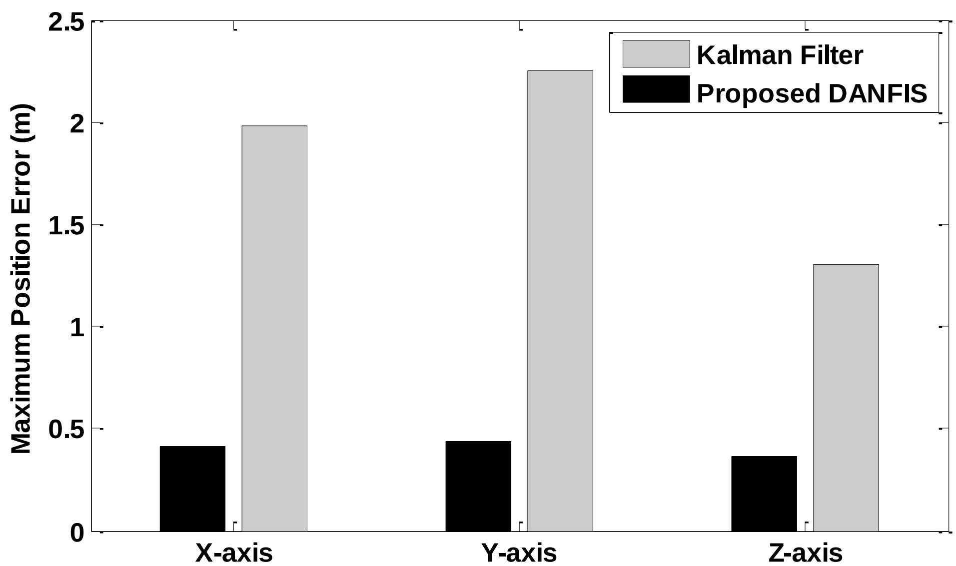
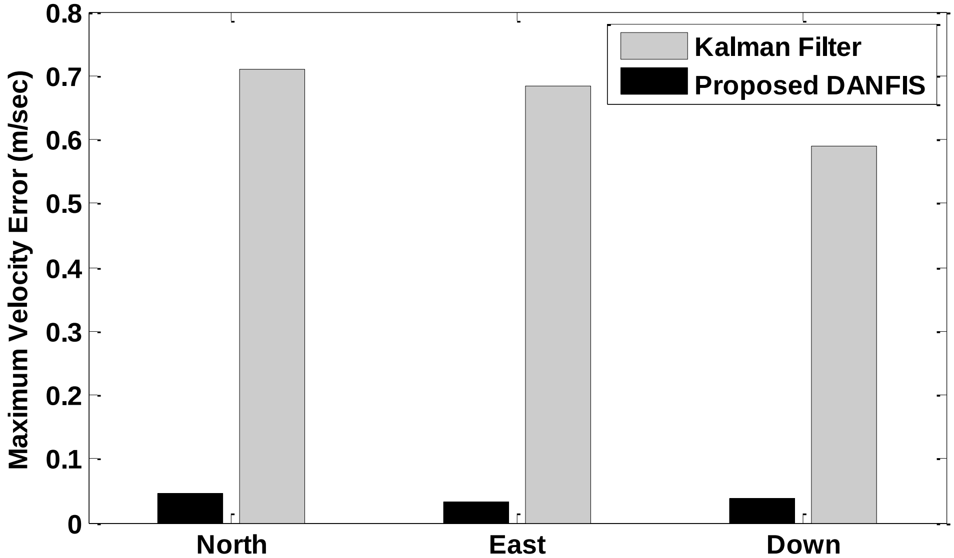


Figure 9. Relationship between the Number of Membership and the Number of Input Delay for all Components in (a) X-Axis, (b) Y–Axis, and (c) Z-Axis for position and (d) North, (e) East, (f) Down directions for Velocity



(a)



(b)

Figure 10. Performance Comparison between the proposed dynamic ANFIS and the Kalman filter for (a) Position, and (b) Velocity

Table 3. Improvement Results for the Proposed DANFIS

		GPS/INS Structure Integration Maximum Error		Improvement %
		KF	DANFIS	DANFIS against KF
Position (m)	x-axis	1.98	0.41	79
	y-axis	2.25	0.44	80
	z-axis	1.3	0.36	72
Velocity (m/s)	North	0.71	0.045	93
	East	0.683	0.033	95
	Down	0.59	0.038	93

5. Conclusions

This paper presents a new DANFIS module to integrate the GPS and INS systems in order to overcome the limitations of the traditional methods and through depending on the previous INS error that has a great effect on the intelligent navigator during prediction mode. However, increasing the number of inputs (i.e. INS data samples) to the ANFIS module will increase the precision of the INS prediction during evaluation phase and increase the time required for learning phase. Therefore, it is better to select a specific number of inputs to the ANFIS to obtain the required accuracy and to keep the time as short as possible. Finally, the results obtained show clearly the superiority of the proposed method compared to Kalman filtering and conventional ANFIS methods.

Acknowledgements

The authors would like to thank the Computer Systems Engineering Research Group at the Universiti Putra Malaysia, 43400 Serdang, Selangor Darul Ehsan, Malaysia, for their continuous help and support. Also, this work was supported in part by the School of Graduate Studies through the Graduate Research Fellowship (GRF). Acknowledgement is also given to the Mobile Multisensor Research Group at the University of Calgary, Calgary, AB, Canada, for providing the experimental data.

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