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Comparing Kalman Filter and Dynamic Adaptive Neuro Fuzzy for Integrating of INS/GPS Systems

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ABSTRACT

Global Positioning System (GPS) and Inertial Navigation System (INS) technologies have been widely used in a variety of positioning and navigation applications. Both Systems have their unique features and shortcomings. Hence, combined system of GPS and INS can exhibit the robustness, higher bandwidth and better noise characteristics of the inertial system with the long-term stability of GPS, Integrated together are used to provide a reliable Navigation System. This paper will compare the performance of Kalman filter and Dynamic adaptive neuro fuzzy system for integrated INS/GPS systems. The Simulation Results by Matlab7 Programming Language showed great improvements in positioning, gives a best results and reduce the root mean square error (r.m.s.) when used Dynamic adaptive neuro fuzzy system rather than Kalman filter.

Keywords: Kalman filter, Dynamic adaptive neuro fuzzy system, GPS System, INS System.

مقارنة كالمان فلترودیناميكية الشبكة المكيفة المضببة لتكامل منظومتي GPS/INS

الخلاصة:

منظومة تحديد الموقع العالمي (GPS) ومنظومة الملاحة ذات القصور الذاتي (INS) تستخدم بشكل واسع في مختلف تطبيقات تحديد المواقع والملاحة .كلا المنظومتين لها ميزات فريدة وعيوب . بتكامل المنظومتين (INS & GPS) نستطيع الحصول على نظام ملاحة متين، نطاق ترددي عالي ، وخصائص ضوضاء أفضل بالنسبة لمنظومة (INS) واستقرارية عالية لمنظومة(GPS). لذلك ،تكامل المنظومتين يستخدم للحصول على نظام ملاحة ذات وثوقية عالية. في هذا البحث تمت المقارنة بين أداء كالمان فلترودیناميكية الشبكة المكيفة المضببة لتكامل المنظومتين. (باستخدام لغة البرمجة Matlab7) حيث تبين تحسينات كبيرة في تحديد المواقع وان r.m.s للخطأ اقل بكثير باستخدام الشبكة المكيفة المضببة بمقارنتها مع نتائج كالمان فلتر .

INTRODUCTION

Since the 1940s, navigation systems, in particular inertial navigation systems (INSs), have become important components in military and scientific applications. In fact, INSs are now standard equipment on most planes, ships, and submarines [1]. However, the INS accuracy degrades overtime due to the unbounded positioning errors caused by the uncompensated gyro and accelerometer errors affecting the INS measurements. Therefore, to obtain very accurate outputs at all frequencies, the INS should be updated periodically using external measurements [2, 3]. On the other hand, the GPS relies on the technique of comparing

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signals from orbiting satellites to calculate position (and possibly attitude) at regular time intervals. But being dependent on the satellites signals makes GPS less reliable than self-contained INS due to the possibility of drop-outs or jamming [4, 5].
The combination of GPS and INS has become increasingly common in the past few years because the characteristics of GPS and INS are complementary. This paper presents two suggested: The first system used Kalman filter to estimate the error of the INS and this estimated error is subtracted from the INS measurement to find the corrected coordinates. In the second system used Dynamic ANFIS Network to predict the INS error during GPS outages based on the current and previous raw INS data. These systems are explained in details in this paper.

Kalman filter

Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) solution of the least-squares method. The filter is very powerful in several aspects: it supports estimations of past, present, and even future states. The Kalman filter is a tool that can estimate the variables of a wide range of processes. The standard Kalman filter is an effective tool for estimation, but it is limited to linear systems. In mathematical terms would say that a Kalman filter estimates the states of a linear system [6, 7].
The basic operation done by the Kalman filter is to generate estimates of the true and calculated values, first by predicting a value, then calculating the uncertainty of the above value and finding an weighted average of both the predicted and measured values most weight is given to the value with least uncertainty. The result obtained the method gives estimates more closely to true values [8].

The Discrete Kalman Filter Algorithm

The Kalman filter estimates a process by using a form of feedback control; the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step [9].

The measurement update equations are responsible for the feedback; i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as shown in figure (1).

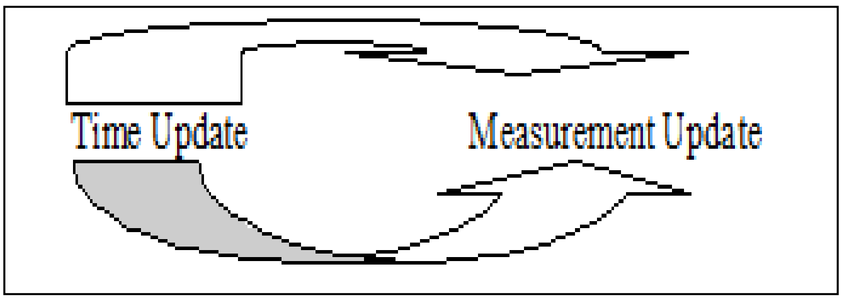


Figure (1): The ongoing discrete Kalman filter cycle.

The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time.
The specific equations for the time and measurement updates are presented below (3, 4 and 5) :

$$X_k^{\wedge -} = A * X^{\wedge}_{k-1} + B * U_k \quad \text{.... (1)}$$
$$P_k^- = A * P_{k-1} * A^T + Q \quad \text{...(2)}$$

The time update project the state and covariance estimates forward from time step to step as in equations:

$$K_k = P_k^- + H^T * (H * P_k^- * H^T + R)^{-1} \quad \text{... (3)}$$

$$X_K^{\wedge} = X_k^{\wedge -} + K_k * (Y_k - H * X_k^{\wedge -}) \quad \text{... (4)}$$
$$P_k = (I - K_k * H) * P_k^- \quad \text{.... (5)}$$

The first task during the measurement update is to compute the Kalman gain, Notice that the equation given here as equation (3). The next step is to actually measure the process to obtain, and then to generate an a posteriori state estimate by incorporating the measurement as in equation (4). The final step is to obtain an a posteriori error covariance estimate via equation (5). After each time and measurement update pair, the process is repeated with the previous a posteriori estimates used to project or predict the new a priori estimates. The Kalman filter instead recursively conditions the current estimate on all of the past measurements.

Dynamic Adaptive Neuro-fuzzy Inference System

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 has the ability to hold the previous INS position and velocity data samples [10, 11].

The use of the shift register with the static ANFIS leads to the dynamic ANFIS that 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 [12].

ANFIS Architecture

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 combines the learning capabilities of a neural network but also incorporates 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) Basic ANFIS architecture that has two inputs (*x*) and (*y*), and one output (*z*) is shown in the rule base contains two Takagi-Sugeno.

According to the ANFIS structure, $O_{l,i}$ is assumed as the output for each layer. Whereas i_{th} the output of the node in l_{th} layer. The ANFIS work for each layer as follows [11]:

Rule 1: If (*x*) is *A1* and (*y*) is *B1*, then $f1 = p1x + q1y + r1$ … (6)

Rule 2: If (x) is $A2$ and (y) is $B2$, then $f2 = p2\,x + q2\,y + r2$ … (7)

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

$$\underline{f(\boldsymbol{x})} = \frac{\sum_{j=1}^{M} y_j * (\mu_{f_j}(y_j))}{\sum_{j=1}^{M} (\mu_{f_j}(y_j))} \quad \ldots (8)$$

Where

M is the number of fuzzy IF-THEN rules, while $\boldsymbol{y_j}$ is the center of fuzzy set $\boldsymbol{f_j}$, that is, a point in the universe of discourse V at which $(\boldsymbol{\mu_{f_i}(y)})$ achieves its highest value, and $(\boldsymbol{\mu_{f_i}(y)})$ 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 (8) becomes [13,14]:

$$\underline{f(\boldsymbol{x})} = \frac{\sum_{j=1}^{M} y_j \ (\prod_{i=1}^{n} (\mu_{f_{ij}}(x_i)))}{\sum_{j=1}^{M} (\prod_{i=1}^{n} (\mu_{f_{ij}}(x_i)))} \quad \ldots (9)$$

Where,

n is the number of input linguistic variables. In order to develop training algorithm for this fuzzy logic system, the functional form of $\boldsymbol{\mu_{f_i}}$ (xi) 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 [15, 16]:

$$\boldsymbol{\mu_{f_i}}(\boldsymbol{x_i}) = \exp\left[-\left[\frac{x_i - m_i}{\sigma_i}\right].\hat{}\,\mathbf{2}\right] \quad \ldots (10)$$

Where;

$\mathbf{m_i}$ and $\boldsymbol{\sigma_i}$ are, respectively, width and center of the $\boldsymbol{i^{th}}$ bell shaped function of the input variable.

From equation (9) and equation (10) the overall function of fuzzy logic system can be obtained:

$$\underline{f(\boldsymbol{x})} = \frac{\sum_{j=1}^{M} y_j \ [\prod_{i=1}^{n} \exp(-\left[\frac{x_i - m_i}{\sigma_i}\right].\hat{}2)]}{\sum_{j=1}^{M} [\prod_{i=1}^{n} \exp(-\left[\frac{x_i - m_i}{\sigma_i}\right].\hat{}2)]} \quad \ldots (11)$$

This equation represents a fuzzy logic system with center average defuzzifier, product inference rule, singleton fuzzifier, and bell shaped membership function. Equation (11) can be embodying as a feed-forward neural network (NN) as exposed in Figure (2). This connectionist model adopted in figure **(2),** 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:

$$O_i^1\,(k) = g(X_i^1\,(k)) \quad \ldots .(12)$$

Where;

g(.) represents the activation function.

The functions of the nodes in each layer of the fuzzy-neural network can be summarized as follows [17]:

Layer 1:

In this layer, every node is an adaptive node with parametric function. The membership grade which represents the brittle value is considered the node output. The equation form of this layer is:

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x+c_i}{a_i}\right|^{2bi}} \quad \text{... (13)}$$

Where; a_i, b_i, c_i represent the parameters set and which is referred premise parameters, represents the linguistic label and x represents the input.

Layer 2:

In this layer, each node is fixed. The output represents the rule's firing strength and the product of the input.

$$O_{L,i} = \omega = \mu(A_i(x)).\mu(B_i(x)) \quad \text{.... (14)}$$

Layer 3:

Each node in this layer is a fixed and computes the ratio of rule's firing strength

$$O_{l,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{.... (15)}$$

Layer 4:

In this layer, the nodes are adaptive and the parameter here called consequent parameters:

$$O_{l,i} = \overline{w}_i\, f_i = \overline{w}_i(p_i\, x + q_i\, y + r_i) \quad \text{.... (16)}$$

Layer 5:

The node in this layer is a single include all signals and the overall output is:

$$O_{l,5}\, \Sigma_i\, \overline{w}_i\, f_i = \frac{\Sigma_i\, w_i\, f_i}{\Sigma_i\, w_i} \quad \text{... (17)}$$

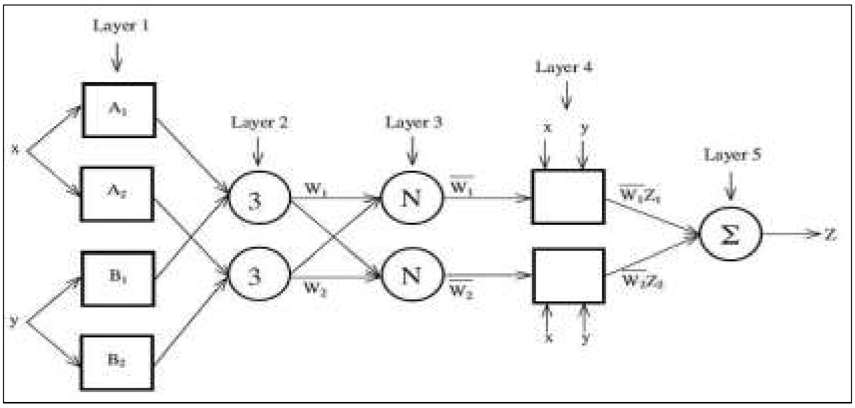


Figure (2): ANFIS Architecture

Where:

x and y are the inputs of ANFIS, Ai , Bi are the fuzzy sets of the inputs, fi (x, y) is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system, pi ,qi , ri are the parameters set, referred to as the consequent parameters. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system [18].

Adaptive Fuzzy System Training Algorithm

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 (11), which minimizes the error function shown below[19,20]:

$$E(k)=\frac{1}{2}\sum_{j=1}^{p}\left[f_j\left(x(k)\right)-d_j\,(k)\right]^2 \quad \text{... (18)}$$

Where;

p is the number of outputs and $\boldsymbol{d_j(k)}$is the $\boldsymbol{j^{th}}$ 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 (18) is reduced to:

$$E(k) = \frac{1}{2}\ (f(x(k)) - d(k))^2 \quad \text{....(19)}$$

Referring to equation (11), if the number of rules in the proposed fuzzy system is M, then the difficulty becomes training the parameters$\boldsymbol{y_j}$, $\boldsymbol{m_{ij}}$, and $\boldsymbol{m_{ij}}$, $\boldsymbol{\sigma_{ij}}$ such that $E(k)$ is diminished. According to the back propagation training algorithm, the iterative equations for training the parameters$\boldsymbol{y_j}$, $\boldsymbol{m_{ij}}$, and $\boldsymbol{m_{ij}}$, $\boldsymbol{\sigma_{ij}}$ are:

$$y_j\,(k+1) = y_j\,(k) - \eta\,(f(\underline{x}\,(k)) - d(k))\,\frac{1}{D}\,O_j^3 \quad \text{.... (20)}$$

$$m_{ij}(k+1) = m_{ij}\,(k) - 2\,\eta\,\frac{z_j}{D}\,(f(\underline{x}) - d(k))*(y_j\,(k) - f(\underline{x}\,(k))*\left[\frac{X_i^2(k) - m_{ij}}{\left(\sigma_{ij}\right)^2}\right] \quad \text{... (21)}$$

$$\sigma_{ij}(K+1) = \sigma_{ij}(K) - 2\eta\frac{z_j}{D}\left(f(\underline{x} - d(K)\right)*(y_j(K) - f(\underline{x}(K))*\frac{(X_i^2(K) - m_{ij})^2}{(\sigma_{ij})^2} \quad \text{... (22)}$$

Where;

η is the learning rate. Equations (20), (21), and (22) perform an error back propagation procedure.

Dynamic adaptive neuro fuzzy Architecture

The DANFIS networks for position components are trained using both the GPS and INS data to construct model related to the instant INS error for the instant and previous INS data samples for position in three axis's (x, y, z). The INS error (desired output) is computed during the GPS availability through subtracting the INS components from the corresponding GPS components for position. These data sets are then used to train DANFIS networks corresponding to the components of position. The inputs for each DANFIS network are the INS data (instant and previous samples) with the instantaneous time. 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 as shown in the figure (3). 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 (20), (21), and (22). 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). 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 (4) [21]:

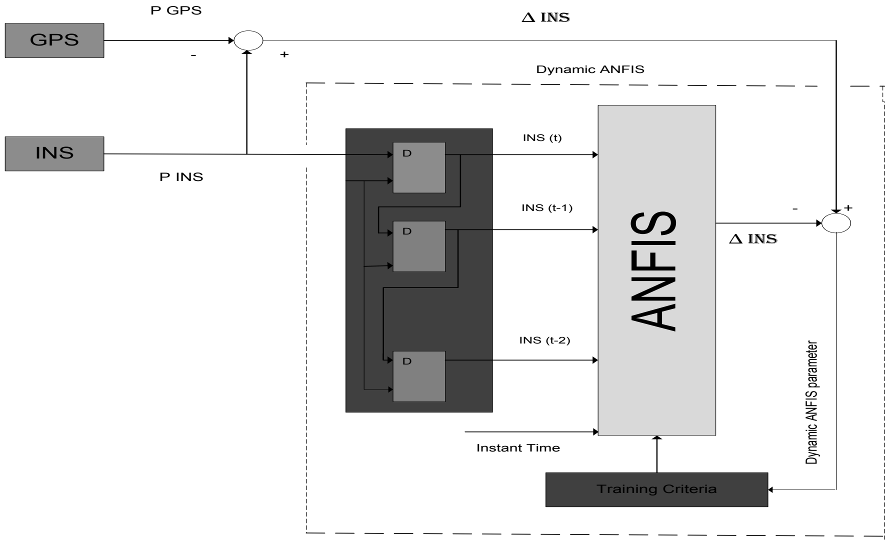


Figure (3): Dynamic ANFIS Scheme for GPS/INS Integration System during updating phase.

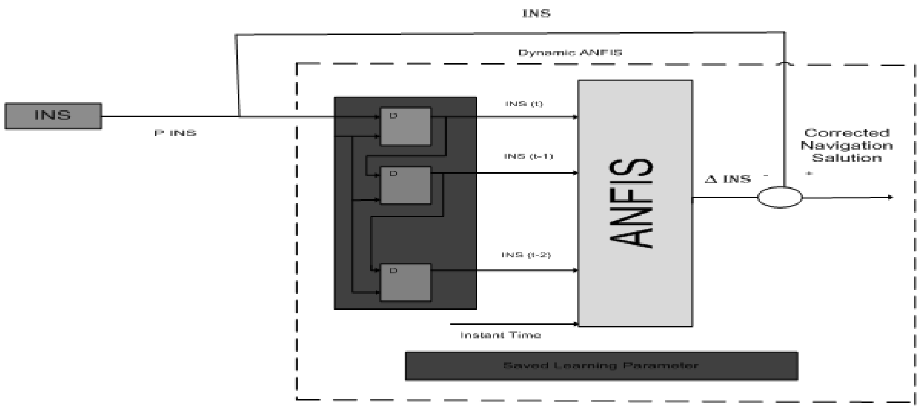


Figure (4) dynamic ANFIS Scheme for GPS/INS Integration system during Evaluation phase

Calculation cases and analysis

For the purpose of comparison between the performance of the two method approach to integrate INS/GPS system, Computer simulation package in Matlab7 are used to estimate the suggested system. Each system represented (X, Y, Z) coordinate by 600 points, in each point the program provides target position (X, Y, Z). GPS predictor gave us 60 points of (X, Y, Z), each of (one second apart), then the predictor output generate 600 points (0.1 second apart), to synchronize with 600 data values from the INS. Results data from GPS & reading value of INS are used to estimate the error of the INS system every 0.1 second. The estimated error is subtracted from INS measurement to obtain corrected INS measurement. Tables (1 (a-c)) represents the r.m.s. error of the integrated INS/GPS for first and second suggested system in the three coordinate (X, Y, Z) respectively.

Tables (1 (a-c)): r.m.s. error of the integrated INS/GPS for first and second suggested system in the three coordinate (X, Y, Z)

Parameters	Integrated INS/GPS used kalman filter of X _axis (m)	Integrated INS/GPS used Dynamic ANFIS of X _axis (m)
RMS Max	15.9812	30.388e-04
RMS Min	0.0262	-2.4262e-04
Variance	14.3740	4.8717e-09
Standard Deviation	3.7913	6.9798e-05

(3a)

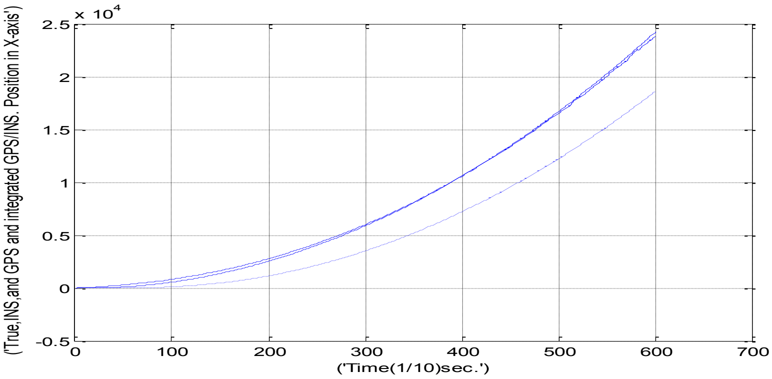
Parameters	Integrated INS/GPS used kalman filter of Y _axis (m)	Integrated INS/GPS used Dynamic ANFIS of Y _axis (m)
RMS Max	72.8690	3.9538e-04
RMS Min	0.0246	-2.6177e-04
Variance	351.5527	5.8250e-09
Standard Deviation	18.7497	7.6322e-05

(3b)

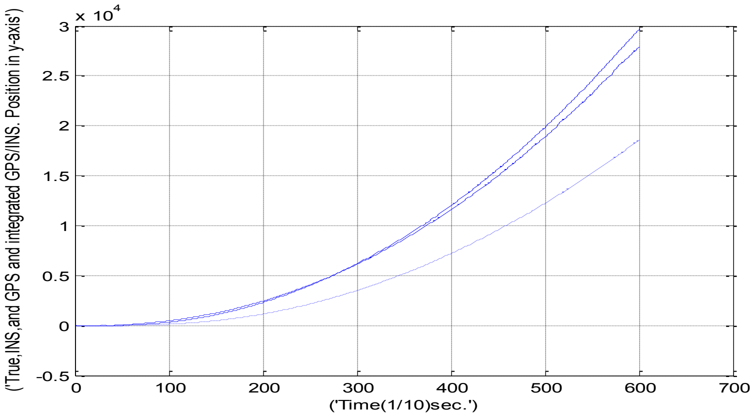
Parameters	Integrated INS/GPS used kalman filter of Z _axis (m)	Integrated INS/GPS used Dynamic ANFIS of Z _axis (m)
RMS Max	900.2392	2.7503e-04
RMS Min	0.1723	-1.7681e-04
Variance	7.2712e+04	4.6733e-09
Standard Deviation	2.69651	6.8361e-05

(3c)

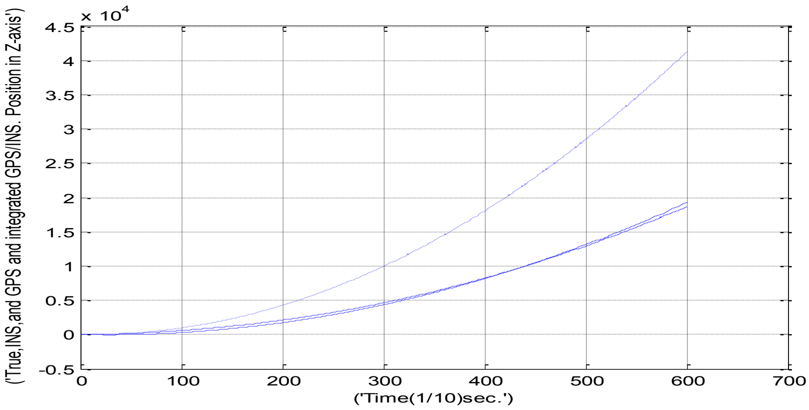
The obtained results shown in Tables (1 (a-c)), show that the dynamic adaptive neuro fuzzy inference system has greater accuracy for integration of INS/GPS system compare with kalman filter method. Figures (5 (a-c)); represent the results of kalman filter method, it shows the exact trajectory of GPS, integrated INS/GPS system and true INS in three axes (X, Y, Z) respectively:



(a): X-axis.



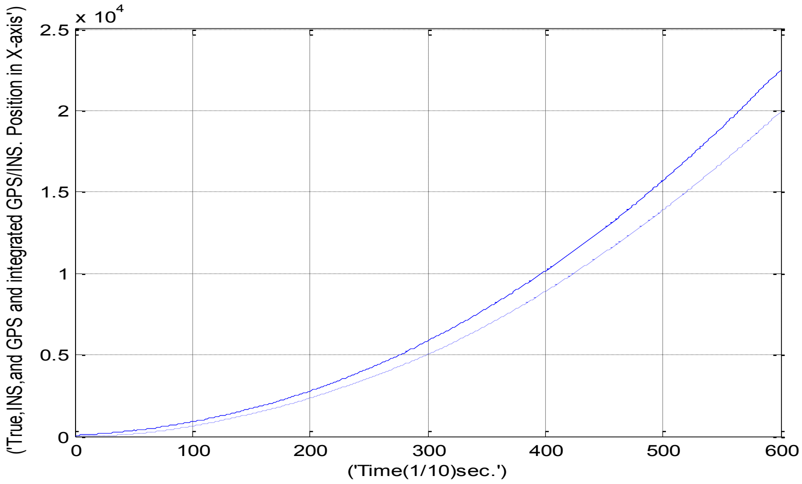
(b): Y-axis



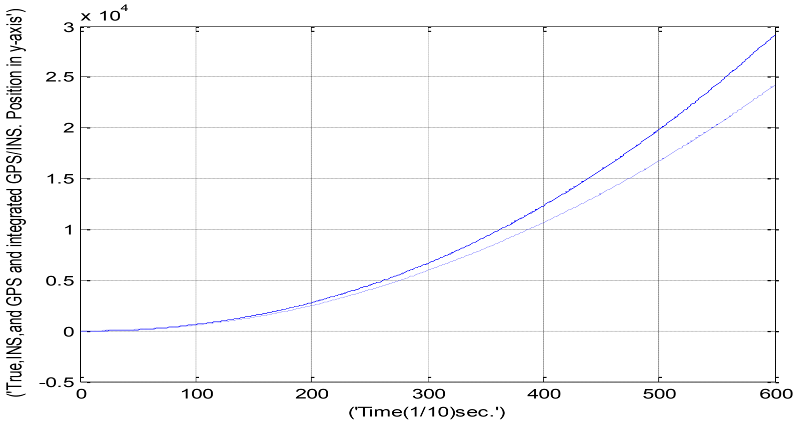
(C): Z-axis.

Figures (5 (a-c)): Results of Integrated INS/GPS using kalman filter method.

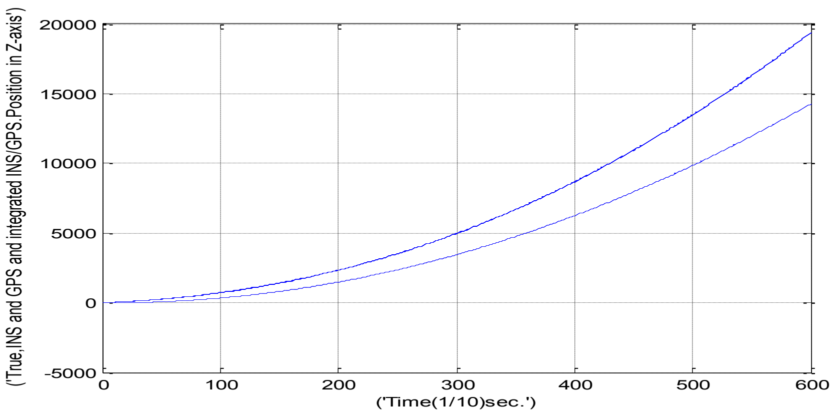
Figures (6 (a-c)); represent the results of dynamic adaptive neuro fuzzy inference system method, it shows the exact trajectory of GPS, integrated INS/GPS system and true INS in three axes (X, Y, Z) respectively:



(a): (X_axis)



(b): (Y_axis)



(c): (Z_axis)

Figures (6 (a-c)): Results of Integrated INS/GPS using dynamic adaptive neuro fuzzy inference system method.

From the above figures and results, the integration results are identical with its exact trajectory of GPS which represent GPS predictor.

DISCUSSION

Different scenarios are taken for both methods; kalman filter and DANFIS to obtain the integration between INS/GPS system in the three coordinates (X, Y, Z), where:

Scenario (I): Tables (1 (a-c)); illustrates the (RMS errors Maximum, Minimum, Variance, and Standard Deviation) parameters, and comparison between kalman filter and DANFIS values in the three coordinate (X, Y, Z).

Scenario (II): Figures (5 (a-c)); represent the results of kalman filter method, it shows the exact trajectory of GPS, integrated INS/GPS system and true INS in three axis (X, Y, Z).

Scenario (III): Figures (6 (a-c)); represent the results of dynamic adaptive neuro fuzzy inference system method, it shows the exact trajectory of GPS, integrated INS/GPS system and true INS in three axes (X, Y, Z).

So, one can see that a very law r.m.s. errors values in the three directions (X, Y, Z) when using DANFIS as compared with kalman filter results and the integration results is identical with its exact trajectory of GPS which represent GPS predictor. Whenever the integration result is identical with exact trajectory of GPS, the INS correction will be more accurate and that is notice when comparing Kalman filter with DANFIS results, which means that DANFIS procedure is more accurate than Kalman filter procedure.

CONCLUSION

This paper presented two proposed methods which are used to integrate INS/GPS system in order to overcome the limitations in both systems. Kalman filter used to estimate the system errors based on the measurement error between the GPS and INS systems, while the DANFIS networks for position components are trained to predict the INS error and compared with the difference between GPS & INS. The difference results then feedback to the network.

A performance test was conducted for DANFIS by taking into consideration the two modes of operation. The first mode during GPS availability by examining DANFIS during updating mode, and the integrated system was also examined during GPS signal lost to validate the capability of the DANFIS model. In conclusion, DANFIS method gives best results and reduced the root mean square (r.m.s) error compared with kalman filter method.

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