Analysis of Different Associative Memory Neural Network for GPS/INS Data Fusion

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Abstract. Aircraft navigation relies mainly on Global Positioning System (GPS) to provide accurate position values consistently. However, GPS receivers may encounter frequent GPS outages within urban areas where satellite signals are blocked. To overcome this drawback generally GPS is integrated with inertial sensors mounted inside the vehicle to provide a reliable navigation solution. Inertial Navigation System (INS) and GPS are commonly integrated using a Kalman filter (KF) to provide a robust navigation solution, overcoming situations of GPS satellite signals blockage. This work presents New Position Update Architecture (NPUA) for GPS and INS data integration. The NPUA has an Artificial Neural Network (ANN) block that uses Associative memoy Neural Networks like Bidirectional Associative Memory Neural Network (BAM-NN) and Hetero Associative memory Neural Network (HAM-NN). The performances of GPS/INS data integration are computed by using HAM-NN and BAM-NN. The performances of both networks are analysed using real time data in terms of Mean Square Error (MSE), Performance Index (PI), Number of Epochs and Accuracy. It is found that HAM is better than BAM in terms of accuracy, MSE, and PI whereas BAM is better than HAM in terms of Number of epochs.

Keywords: HAM-NN, BAM-NN, GPS, INS, KF, ANN, DR.

1 Introduction

1.1 Global Positioning System

The Global Positioning System (GPS) is part of a satellite-based navigation system developed by the U.S. Department of Defense under its NAVSTAR Satellite program. The fully operational GPS includes 24 or 28 active satellites approximately uniformly dispersed around six circular orbits with four or more satellites each. Theoretically, three or more GPS satellites will always be visible from most points on the earth's surface, and four or more GPS satellites can be used to determine an observer's position anywhere on the earth's surface 24 hours per day [14]. The GPS is accurate and the accuracy does not degrade with time but still it suffers from its own drawbacks and errors. It uses the energy of the radio waves for obtaining the navigation parameters hence it is prone to jamming. Also the signal may get obstructed in urban areas due to tall buildings and other obstacles [2]. GPS provides three positional components. The three positional components are along the East direction (corresponding to the vehicle's longitude), the North direction (corresponding to the vehicle's latitude) and the vertical direction (corresponding to the vehicle altitude h).

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1.2 Inertial Navigation System

An Inertial Navigation System (INS) is a self-contained system that integrates three acceleration and three angular velocity components with respect to time and transforms them into the navigation frame to deliver position, velocity, and attitude components [2]. The three orthogonal linear accelerations are continuously measured through three-axis accelerometers while three gyroscopes monitor the three orthogonal angular rates in an inertial frame of reference. In general, inertial measuring unit (IMU), which incorporates three-axis accelerometers and three-axis gyroscopes, can be used as positioning and attitude monitoring devices. However, INS cannot operate appropriately as a stand-alone navigation system. The presence of residual bias errors in both the accelerometers and the gyroscopes, which can only be modeled as stochastic processes, may deteriorate the long-term positioning accuracy. Therefore, the INS/GPS integration is the adequate solution to provide a vehicular navigation system that has superior performance in comparison with either a GPS or an INS stand-alone system.

1.3 Existing INS/GPS Data Fusion Techniques

In order to overcome the problems associated with the operation of GPS and INS on their own, the two systems are integrated together so that the drawbacks associated with each system are eliminated. The INS/GPS data integration is commonly performed in real time using a Kalman filter (KF) [10]. This method requires a dynamic model of both INS and GPS errors, a stochastic model of the inertial sensor errors, and *a priori* information about the covariances of the data provided by both systems. Data fusion employing a KF has been widely used and is considered the benchmark for INS/GPS integration [11].

There are, however, several considerable drawbacks to its use [10]. These include the following: (1) the necessity of accurate stochastic modeling, which may not be possible in the case of low cost and tactical grade sensors; (2) the requirement for *a priori* information of the system and measurement covariance matrices for each new sensor, which could be challenging to accurately determine; (3) relatively poor accuracy during long GPS outages; (4) the weak observability of some of the error states that may lead to unstable estimates of other error states ; and (5) the necessity to tune the parameters of the stochastic model and the *a priori* information for each new sensor system. The above drawbacks can be overcome by using intelligent networks or Artificial Neural Networks (ANN) ([3], [4]). Other than Kalman filter there are also number of paper works related to GPS and INS data integration using soft computing techniques. GPS and INS data integration has been performed using Radial Basis Function Neural Network, Back Propagation Neural Network and Fuzzy system.

Radial Basis Function Neural Network (RBF-NN) generally has simpler architecture and faster training procedure than multi- layer perceptron neural networks ([1], [2], [6], [8], [10]). Though it has simple architecture and faster training procedure, it only has fixed topology, so it lacks dynamicity. Back Propagation Neural Network is one of the Multi-Layer Feed Forward Networks. Although it has batch update of weight which provides smoothing effect on the weight correction terms it only has fixed topology, so it lacks dynamicity ([1], [5]). It also consumes longer training time for complex problems. Fuzzy system can also be used to integrate

GPS and INS data but it does not have much learning capability [7]. It cannot examine all input and output for complex problems. It needs human operator to tune fuzzy rules and membership function.

1.4 Proposed GPS/INS Data Fusion Technique

The proposed data fusion technique introduces New Position Update Architecture (NPUA) which involves Artificial Neural Network in it. It is derived from the concept of Position Update Architecture (PUA) [5]. The NPUA can act in both prediction mode and training mode.

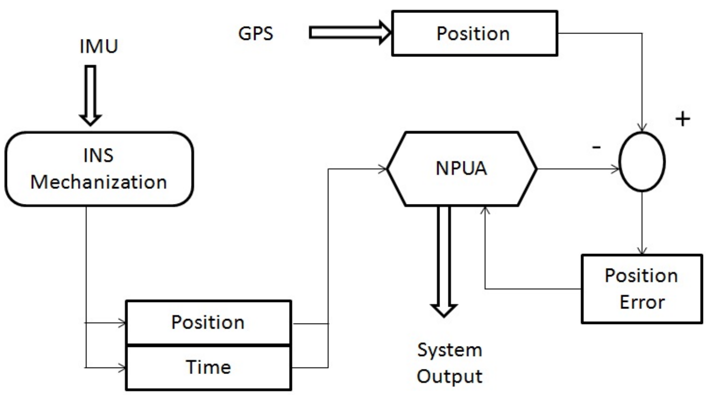

Fig. 1. System Configuration of Proposed Scheme

The NPUA receives input like position and time through INS Mechanization. Desired outputs are provided by the system in training mode when there is no GPS blockage with the help of the appropriate training algorithm. During the training mode of NPUA the initial error is stored the network. When there is GPS signal blockage, the system output operates in prediction mode. During the prediction mode of NPUA , the system makes use of the initial error stored and thereby predicts the accurate position values. The proposed system configuration is shown in Figure 1. The HAM-NN and BAM-NN are used in NPUA.

2 Neural Networks Used in GPS/INS Data Fusion

There are many different types of ANN according to its inherent structure and learning algorithms. The choice of the type of ANN depends on its suitability to a particular application. In this work, HAM-NN and BAM-NN have been implemented using Delta Learning Rule (DR).

2.1 Hetero Associative Memory Neural Network

Associative memory neural networks are networks in which the weights are determined in such a way that the net can store a set of P pattern associations.

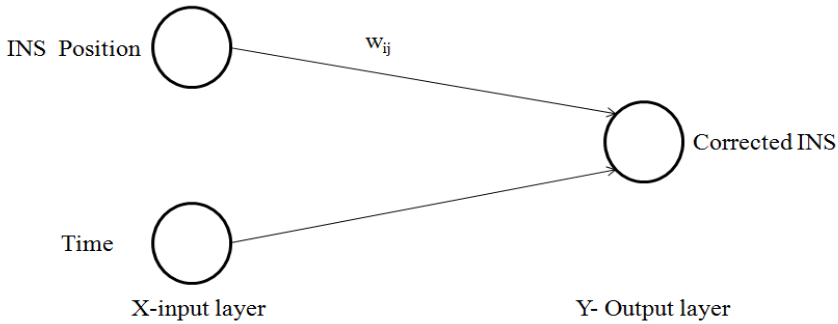

Fig. 2. GPS/INS Data Fusion using HAM

Hetero associative networks are static networks. No non-linear or delay operations can be done using hetero associative networks. The weights may be found using the Hebb rule or the delta rule. Hetero Associative Memory Neural Network is a Two - layer network with input and output layer. The design of a HAM-NN in its most basic form consists of two separate layers as shown in Figure 2 is used in GPS/INS data fusion.

It consists of only one layer of weighted interconnections. There exist 'n' number of input neuron in input layer and 'm' number of output neurons in the output layer. The training process is based on the Hebb learning rule. This is a fully inter-connected network, wherein the inputs and the output are different, hence it is called a hetero associative network.

2.2 Application Algorithm for HAM

The weights of the network are obtained using the training algorithm. These weights are used along with the testing data and the performance of the network is tested by applying the following application procedure ([12], [13]). The application procedure of a hetero associative net is as follows:

Step 1: Weights are initialized using Hebb or delta rule.
Step 2: For each input vector do steps 3 to 5.
Step 3: Set the activation for input layer units equal to the current vector x_i.
Step 4: Compute net input to the output units

$$Y\text{-}inj = \Sigma\ xiwij \quad (1)$$

Step 5: Determine the activation of the output unit.

The simple and frequently used method for determining the weights for an associative memory neural network is Hebb rule(HR). The other learning rule that can be used Associative memory is Delta Learning Rule (DR). The algorithm for DR is as follows:

Step 1: Initialize all weight to random values.
Step 2: For each training input-target output vector, do steps 3-5.
Step 3: Set activations for input units to present training input.

Step 4: Set activations for output units to current target output.
Step 5: Adjust the weights.

$$wij(new) = wij(old) + \Delta w \quad (2)$$

Weight correction

$$\Delta w = \alpha(tj - y\ inj)xi \quad (3)$$

Where i= 1 to n, j= 1 to m
t- target vector,
y_{inj} – actual output vector
α- learning rate.

2.3 Bidirectional Associative Memory Neural Network

BAM-NN is a hetero associative recurrent neural network consisting of two layers. The net iterates by sending a signal back and forth between the two layers until each neuron's activations remains constant for several steps ([9], [15]).

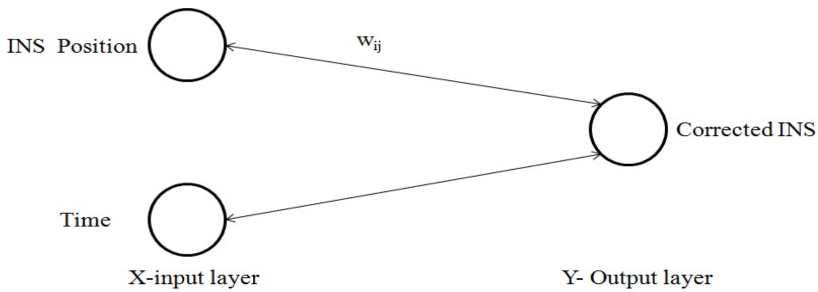

Fig. 3. GPS/INS Data Fusion using BAM

The hetero associative BAM network has 'n' units in X-layer and 'm' units in the Y-layer. The connections between the layers are bidirectional i.e. if the weight matrix for signals sent from the X-layer to Y-layer is W, the weight matrix for signal sent from Y-layer to X-layer is W^T. The architecture is shown in figure 3 is used in GPS/INS data fusion.The weights are adjusted between X-layer to Y-layer and also from Y-layer and X-layer.

2.4 Application Algorithm for BAM

The application procedure of bi-directional memory net is as follows:

Step 1: Initialize all weight to store a set of P vectors. Initialize all activations to 0.
Step 2: For each training input-target output vector, do steps 3-8.
Step 3: Set activation of X-layer to current input pattern.
Step 4: Input pattern y is presented to the Y-layer.

Step 5: While activations are not converged follow steps 6-8.
Step 6: Activation unit in Y-layer and net input are computed.

$$\text{Net Input, } y_{-inj} = \sum_i w_{ij} x_i \tag{4}$$

$$\text{Activation } y_i = f(y_{-inj}) \tag{5}$$

Send signals to the X-layer.
Step 7: Update activation unit in X-layer.

$$\text{Net input, } x_{-inj} = \sum_i w_{ij}^T y_j \tag{5}$$

$$\text{Activations } x_i = f(x_{-inj}) \tag{6}$$

Send signals to the Y-layer
Step 8: Test for convergence.

3 Simulation Results

3.1 Experimental Setup

In this experiment, the training mode and prediction mode of HAM-NN and BAM-NN were utilized in NPUA. During the presence of GPS signal, the proposed system relies on GPS position information to train the network. During the training stage, the HAM-NN module and is trained to mimic the latest vehicle dynamic, determine the INS position error, and correct the corresponding INS position component. The data is processed as follows: first, the INS and GPS signals are taken as input vector and target vector respectively. The INS position and time are then used as the input to HAM-NN and BAM-NN respectively. Then training is done until the output nearly equals the target GPS position. The training procedure continues working until GPS signal blockage is detected. When blockage is detected, the proposed system works in the prediction mode where the HAM-NN module and BAM-NN module predicts the corresponding INS position error based on the knowledge stored during the training procedures. Then with the help of the INS position error obtained during the training mode the corresponding corrected INS position is obtained during the absence of GPS, i.e, during the prediction mode.

3.2 Simulation Results

GPS position value is used as target vector value and INS position value is used as input vector in Mat lab. By training the HAM-NN module and BAM-NN module for latitude component figure 4 and 5 are obtained. In figure 4 and 5 latitude component is taken as x-axis and time is taken as y-axis. By comparing the actual output and target output the weight values all ANN values are updated using DR. Further the training is done if the actual output is not closely equal to the required target output. After each epoch the weight values are updated. The training proceeds until the stopping condition is reached. The stopping conditions can be number of epochs or minimum error.

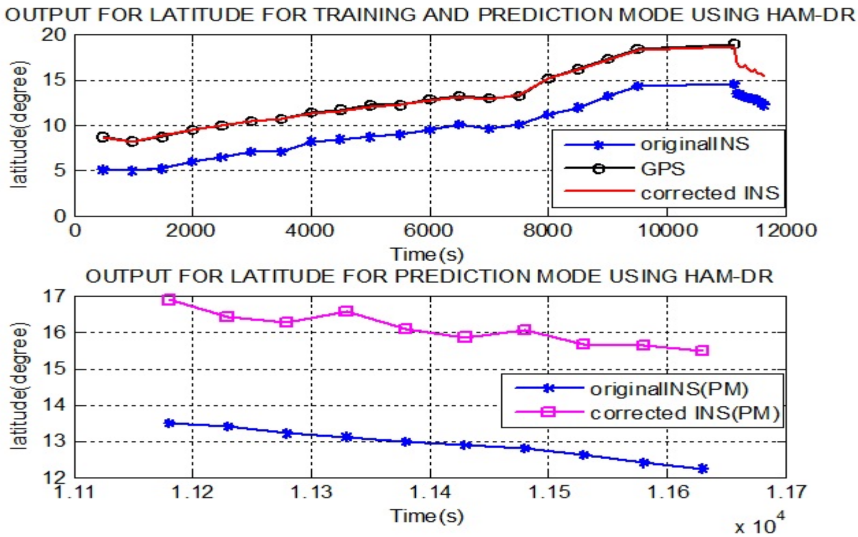

Fig. 4. Output of latitude component using HAM-NN

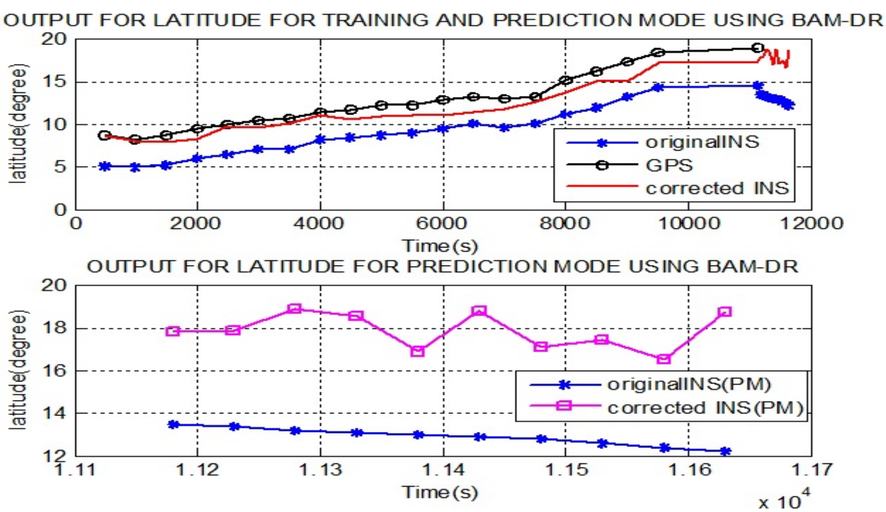

Fig. 5. Output of latitude component using BAM-NN

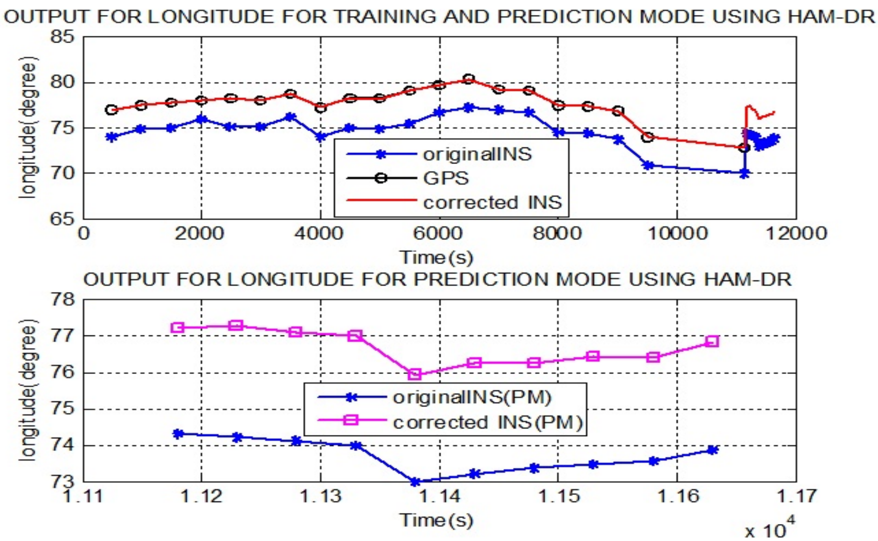

Fig. 6. Output of longitude component using HAM-NN

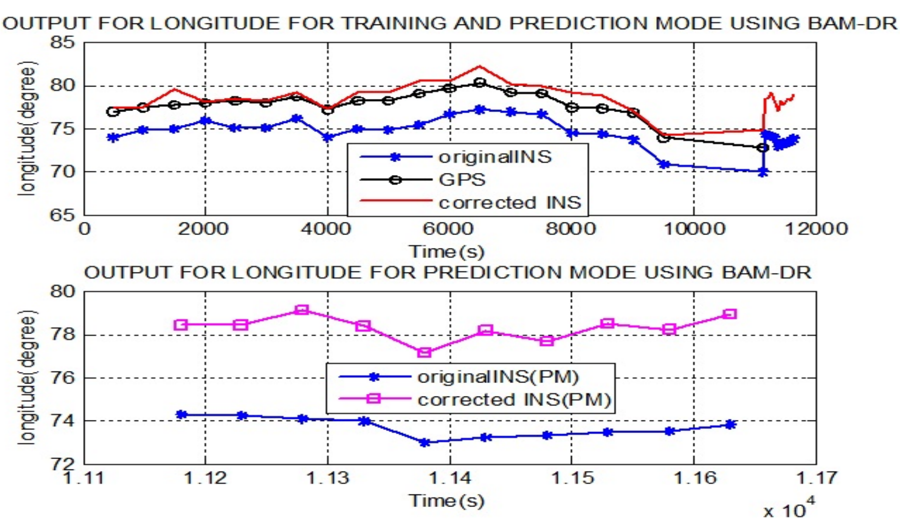

Fig. 7. Output of longitude component using BAM-NN

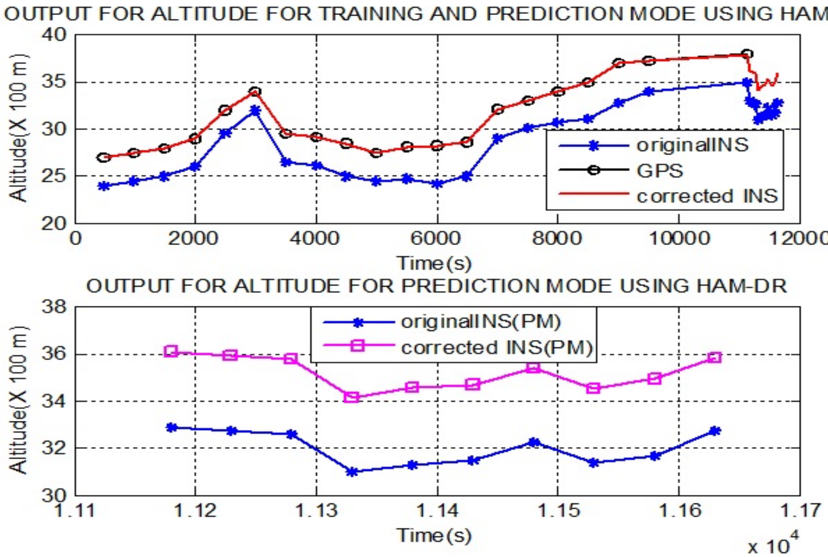

Fig. 8. Output of altitude component using HAM-NN

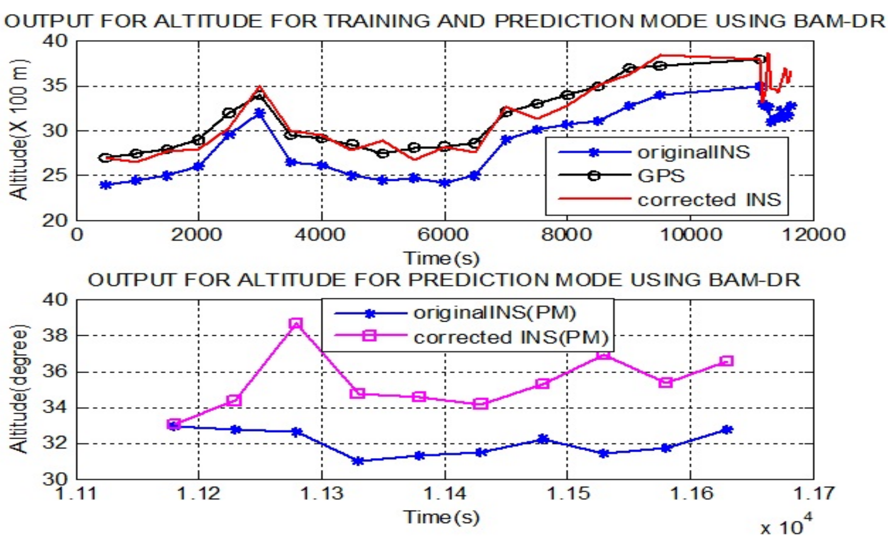

Fig. 9. Output of altitude component using BAM-NN

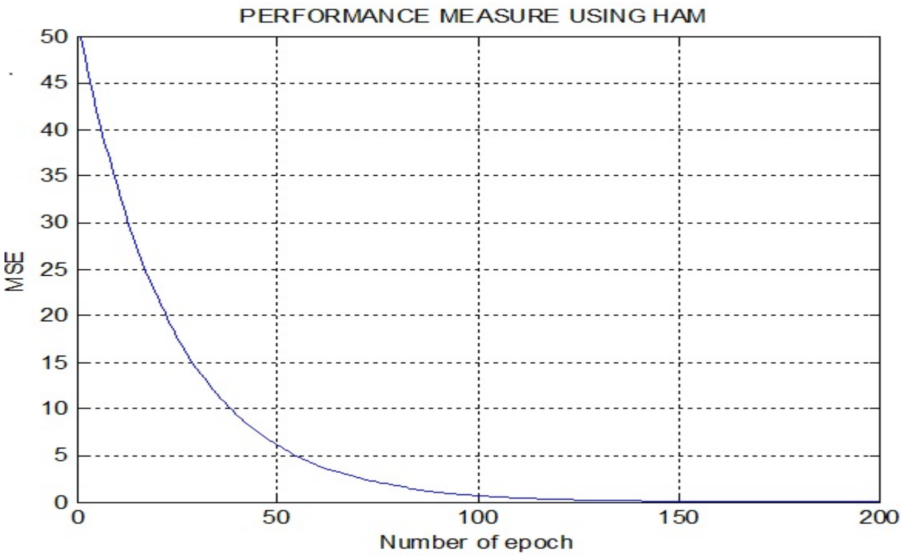

Fig. 10. HAM Performance for latitude component using TM

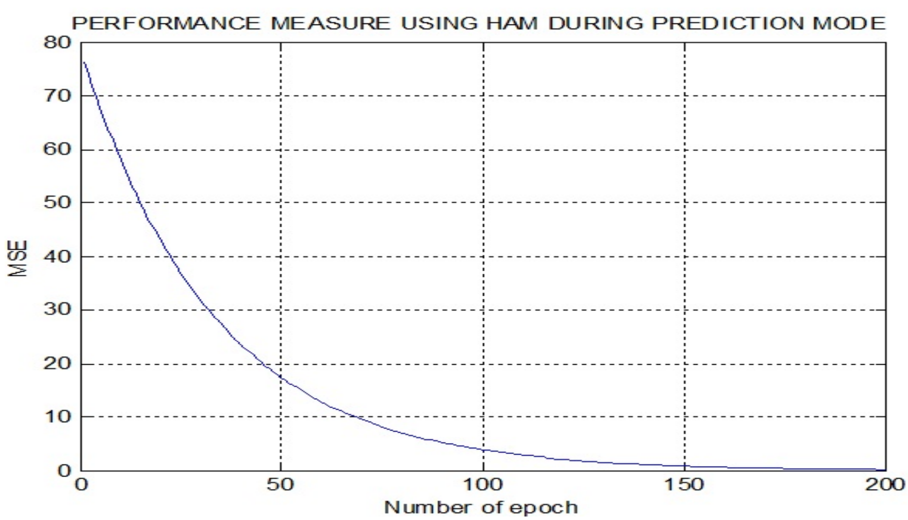

Fig. 11. HAM Performance for latitude component using PM

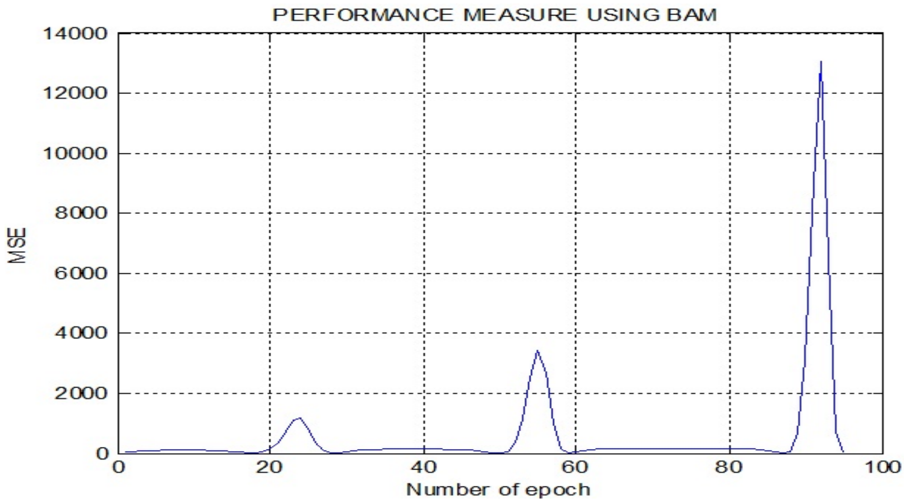

Fig. 12. BAM Performance for latitude component using TM

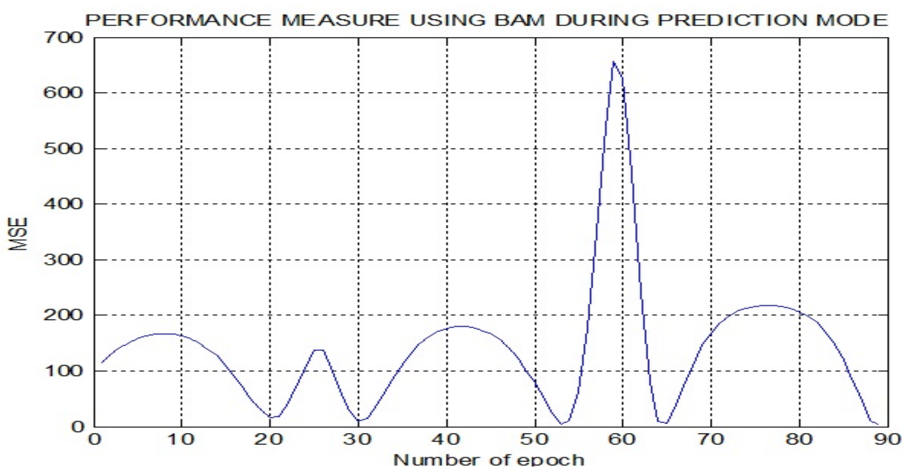

Fig. 13. BAM Performance for latitude component using PM

Similar to latitude component, the longitude component and altitude component is trained using HAM-NN, BAM-NN by choosing the appropriate weight factor and same learning rate value as used for latitude component. The output of longitude and altitude component obtained using HAM-NN and BAM-NN are given in figure 6, 7, 8 and 9 respectively. After each and every epoch error between the original GPS position and corrected INS are calculated in both ANN modules.

Table 1. Numerical values of analysis

Criteria	HAM-NN (TM)	HAM-NN (PM)	BAM-NN (TM)	BAM-NN (PM)
Latitude MSE	0.0096	0.1859	1.4105	2.5449
Longitude MSE	0.0010	0.0048	1.1411	2.9511
Altitude MSE	0.0012	0.0031	0.9534	2.6700
Latitude PI	0.0053	0.0074	0.1120	0.1543
Longitude PI	$2.999e^{-5}$	$3.0297e^{-5}$	0.0147	0.0385
Altitude PI	$4.0645e^{-5}$	$4.9147e^{-5}$	0.0306	0.0759
Latitude NE	200	200	95	89
Longitude NE	12	10	6	6
Altitude NE	49	49	14	15

The mean square error value for each epoch is also calculated. The mean square error graphs using HAM and BAM for latitude component are given in figure 10, 11, 12, 13, respectively. In these graphs number of epochs is taken as x-axis and MSE value is taken as y-axis. The MSE, PI and Number of Epochs for all the three components are given in Table 1. In HAM-NN, it is found that more number of epochs is needed when compared to that of BAM-NN. Whereas BAM-NN is less accurate when compared to HAM-NN. It is also found that as the number of epochs increases the actual output i.e., CINS value of ANN training comes closer to the target output i.e., GPS value.

4 Conclusion

Thus from the results it was found that INS and GPS data Fusion can be performed by using Associative memory NN. HAM-NN using DR gives higher accuracy in both Training Mode (TM) and Prediction Mode (PM) when compared to BAM-NN using DR. Similarly HAM-NN using DR gives lesser MSE value in both Training Mode (TM) and Prediction Mode (PM) when compared to BAM-NN using DR. In terms of Performance Index (PI), HAM-NN using DR has lesser PI value, whereas BAM-NN using DR has higher PI value than PI values of HAM-NN using DR. Only the neural network lesser PI value can show better performance, so it can be found that HAM-NN using DR is better in terms of performance. Though HAM-NN using DR is good in terms of MSE, PI and accuracy, but it consumes more number of epochs. Thus, by considering MSE, PI and accuracy, it can be concluded that HAM-NN using DR can be used to fuse GPS and INS data. If the data fusion system requires lesser number of epochs, BAM-NN using DR can be used to fuse GPS and INS data.

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