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Integration of Global Positioning System and Inertial Navigation System with Different Sampling Rate Using Adaptive Neuro Fuzzy Inference System

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Abstract: Integration of the Global Positioning System (GPS) and Inertial Navigation System (INS) has become increasingly common in the last two decades, because the characteristics of GPS and INS are complementary and the integration between both systems will maximize their advantages and minimize their weakness. Over time, inertial navigators drift from their preset alignments. Or, the initial alignment may have been corrupted by vehicle motion, with imperfect transfer of alignment and velocities to the navigator. Also, there may not have been enough time to perfect alignment. In such case, navigators can be benefit from aiding such as GPS. The integration between the GPS and INS leads to accurate navigation solution by overcoming each of their respective shortcomings. And to make this integration possible the difference between the GPS and INS systems in sampling rate must be solved before any integration can be work properly. In this paper, the GPS low rate problem is solved by predicting or extrapolating the mislaid reading data of the GPS to be attuned with those of INS data using Adaptive Neuro Fuzzy Inference System (ANFIS). Hence, the gap between the two systems reading data is solved to provide synchronization between the INS and GPS systems. So, it is possible to compare the reading data of both systems. Three strategies have been proposed and the results shows superior performance in predicting missed GPS data with lowest mean error.

Key words: Global Positioning System (GPS) . Inertial Navigation System (INS) . Adaptive Neuro fuzzy Inference System (ANFIS) . navigation systems . sampling data rate

INTRODUCTION

GPS is a constellation of satellites developed by the United States Department of Defense military as a navigation utility. First launched in 1982 and fully operational since 1990, GPS satellites have become increasingly important to both military and civilian navigation. They use one-way ranging as their fundamental navigation technique [1].

GPS is capable of providing precise positioning information to an unlimited number of users anywhere on the planet. However, GPS can provide this type of information only when there is a direct line of sight to four or more satellites. Regrettably, this requirement is not constantly possible since a GPS signal may be lost when moving around obstacles (in canopy, urban areas, inside tunnels, between large building and tree lined streets, etc), or signal jamming by an adversary forces or bad weather conditions. Therefore overall GPS accuracy degrades regarding the above reasons. In other words, the system does not work properly in urban areas due to signal blockage and attenuation that may deteriorate the overall positioning accuracy [2-4]. On the other hand, navigation systems, in particular inertial navigation systems (INSs), have become important components in different military and civil applications. INS is a self-contained system that consists of two set of sensors three orthogonal accelerometers and three orthogonal gyroscopes, which measure three linear accelerometers and three angular rates, respectively. These measurements need to be processed to get position and velocity information [5]. Regrettably, the INS cannot substitute the GPS or operate as a standalone system. During the mechanization of processing the IMU output, the accuracy of INS solution deteriorate with time due to the inherent sensors errors that reveal considerable long-term error growth in position and velocity [6, 7]. These long-term errors including white noise correlated random noise, bias instability and angle random walk. Also, It must be mentioned that there errors are stochastic in nature and can cause a significant

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degradation in the INS performance over a long period of operation. Therefore INS and GPS are often paired together in order to provide a navigation system that has superior performance in comparison with either a GPS or an INS standalone system.

There are many GPS applications, including air, land, and marine navigation, precision agriculture, surveyingand precise timingand there are different receivers specific to each application [8].

BACKGROUND

The last two decades have shown an increasing trend in the use of navigation technologies in several applications including land vehicles and automated car navigation. Navigation systems incorporate the Global Positioning System (GPS) and the Inertial Navigation System (INS) both can be used for wide range of navigation functions. Each has its strength and weaknesses. This work aims to provide a high superiority method to aggregate different data rate GPS with INS data without sacrificing performance even if using low cost inertial sensors.

The INS and GPS are different in the sampling rate because the INS is very fast system, which produces data at a high data rate, compared to the GPS receiver which is slower than the INS. Hence, there is gab between the two systems reading data. Some researchers overcomes this problem by choosing the GPS and INS systems with the same sampling rate as in [9], or using kalman filter to predict the sampling between instants as in [10]. Furthermore, There are several significant drawbacks related to kalman filter such as the requirement for a priori information of the system and measurement covariance matrices for each new sensor, that could be tough to accurately verified, another typical problem related to kalman filtering is the observability of different states, therefore weak observability of some of the error states that may lead to unstable estimates of another error states [7, 11-14]. While the proposed intelligent predictor is general and not depend on the type of the sensor, from the literature it is obvious that there is a lack of research that focus on considering or solving this problem while solving it will open a wide range of flexibility to integrate different rate systems such as GPS and INS of any type with different sampling rate. In this paper we will use Adaptive Neuro fuzzy Inference System (ANFIS) to predict the sampling of GPS data between instants. Most of the researchers provoked to investigate an alternative approach to the KF due to the inadequacy of the KF, in this paper artificial intelligence chosen to be the hard core of the intelligent predictor. Multi-layer Perceptron (MLP) neural networks have been used by many researchers in different fields [3, 15, 16]. However, MLP neural networks have some problems, such as their black-box nature, the lack of knowledge representation powerand the selection of the proper structure and size to perform the required real time implementation. ANFIS were chosen as the core for the new predictor integration technique for several reasons: (1) rapid ability of input and output mapping, therefore, well-matched for mapping the GPS data as input to extrapolated missing data as outputs; (2) the proposed modeless system requires no prior knowledge of the GPS sensor information and hence increase the ability for learning process; (3) ANFIS is a fixed simple structure with reduced computation resources leading to real time implementation. Hence, ANFIS is more simplest compared to MLPNNs that need to determine the optimal number of hidden layer and number of neuron's in each layer [17, 18].

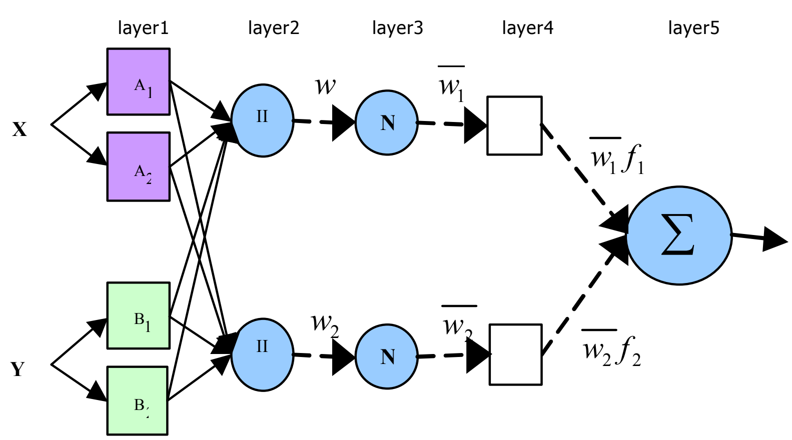

Fig. 1: Schematic of the Neuro-fuzzy model [19]

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is an adaptive network based on fuzzy inference systems. It combines fuzzy logic and neural networks to facilitate the hybrid learning procedure. ANFIS architecture consists of five consecutive layers as illustrated in Fig. 1 [19].

Each layer consists of a number of nodes (i) that perform different operation according to the internal node function. The first layer contains a number of Membership Functions (MFs) associated with each input variable to project the input parameters into the fuzzy domain. Each membership function is defined by a set of non-linear parameters. Known as the antecedent parameters $\{a_i, b_i, c_i\}$. Each node in the second layer operates a multiplication between the signals coming from the first layer and provides the product (w_i) for the following layer. The third layer normalizes the output of each nodes of the pervious layer with respect to the total output of all nodes ($\overline{w_i}$). Nodes in the fourth layer contain functions with a set of linear parameters known as consequent parameters $\{p_i, q_i, r_i\}$. These parameters are estimated during the forward propagation using least square method. The last layer sums all incoming signals and provides the overall outputs.

ANFIS utilizes a hybrid learning technique, in which there are two main algorithms involved. First is the feed forward propagation, which based on least square adjustments to estimate the consequent parameters, defined in layer 4. The second algorithm is the feed backward propagation that is based on the gradient descent optimization technique to adjust (update) the antecedent membership function parameters. The forward propagation represents the fuzzy reasoning, while the backward propagation represents the neural computations. In the following subsections is a detailed description of the ANFIS process starts with the clustering data set at the input layer and describing both the feed forward and backward propagation procedures.

Input data clustering: Input data sets are clustered into a number of partitions such that the likeness within each partition is larger than the likeness among the partitions. This clustering is used mainly to determine the location of membership function, thus, it provides fast and accurate generation of the fuzzy relationship between the input and output data sets. Generally, increasing the number of MFs guarantees high resolution of mapping the input variables. Such high resolution is necessary to capture the high dynamic that might exist in the input data. In this work, the subtractive clustering method is used. Subtractive clustering requires no prior knowledge of the number of the clusters. It only requires the cluster radius, which indicates the range of the influence of a cluster and hence determines the number of the antecedent membership functions [20].

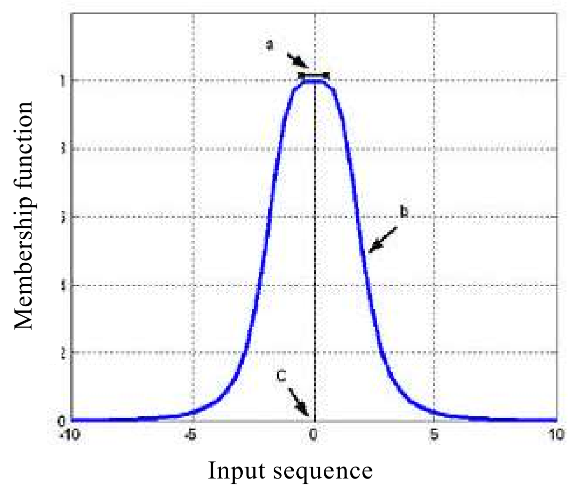

Fig. 2: Generalized bell membership function

For n input data points $\{x_1, \ldots\ldots, x_n\}$, each one is assumed as a candidate for cluster centers. The density measure at each data point x_i is, then, computed as follow [20]:

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\left\| x_i - x_j \right\|^2}{(r_a/2)^2} \right) \quad (1)$$

where r_a is a cluster radius and it is the only external parameter required for this process. Data point of a highest density measure D_{c1} indicates many near data points in the neighborhood, and hence is selected as the center of the first cluster x_{c1}. The second cluster center, then, is derived by computing the density measure again, but with the following revised expression [20]:

$$D_i = D_i - D_{c1} \exp\left(-\frac{\left\| x_i - x_{c1} \right\|^2}{(r_b/2)^2} \right) \quad (2)$$

where r_b is selected equal to 1.5 r_a to prevent closely spaced cluster centers. In Equation 2, data points near to the center of the first cluster have less density measure and thus unlikely to be selected as a center of the next cluster. As with the first cluster center, the highest density measure is computed by Equation 2 and is selected as the second cluster center. This step is repeated until a number of cluster centers are derived to adequately group the input data set.

Clustering the input data set is the first process to accurately determine the number of fuzzy membership functions and the initial parameter of each membership function. These parameters are updated using the gradient descent optimization technique through the backpropagation algorithm [19]. The following step to the clustering the input data set is the fuzzification of this data set.

Mapping input data set into fuzzy domain: The number of the membership functions derived by the subtractive clustering method is based on initial antecedent parameters for each membership function as presented in Fig. 2. These antecedent parameters highly affect the output of each function and hence they shall be updated in order to provide the desired input-output relationship.

In this step, the input variables (crisp inputs) are mapped into the fuzzy domain using the membership functions (MFs). Bell shape MF was used here. Function parameters {*a, b, c*} of the bell shape MFs determine the width, spread and center of the MF respectively as in the following expression.

$$w_i(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \quad (3)$$

Where x is the input variable and w_i (x) is the membership (weight) of the input variable x to the fuzzy set i.

Least square adjustments in feed forward propagations: The normalized weights $\overline{w_i}$ are the output of layer 3 and are used to determine the desired output y of layer 4.

$$y = \sum \overline{w_i} f_i = \sum \overline{w_i}(p_i \ x + q \ y + r_i) \quad (4)$$

Where are {p_i, q_i, r_i} the linear unknown consequent parameters estimated using the method of the least squares [21].

Gradient descent in feed backward propagations: The antecedent parameters of the membership functions are updated during the feed backward propagation. This backward propagation is based on the gradient descent optimization algorithm [22]. This method is the most frequently used in nonlinear optimization technique due to its simplicity. The steepest descent formula is presented as follow:

$$\theta_{k+1} = \theta_k - \eta g \quad (5)$$

where θ is the antecedent parameters {*a, b, c*}, k is the epoch number, η is the step size parameter, g is the gradient of the network error with respect to the antecedent parameters. The network error is defined as a square sum of difference between the network output and the desired output. Therefore, using an input-output data set allows the backpropagation algorithm to update the antecedent membership function parameters.

The step size parameter η affects the convergence time of the input-output mapping process. If η is chosen too small, the convergence time will be slower and if chosen too high, the algorithm might not be stable. The ANFIS algorithm is implemented using MATLAB environment by writing a specific program for this purpose. The algorithm allows changing the initial step size during training based on the error measure of the ANFIS prediction.

In summary, the paramount advantage of ANFIS is using the hybrid learning algorithm to train the network parameters. During the forward pass, the functional signal feed till layer 4, and then the linear consequent parameters are estimated using least squares estimates. In the backward pass, backpropagation algorithm is used to determine the antecedent parameters while the consequent parameters are kept fixed.

THE PROPOSED ANFIS FOR GPS DATA PREDICTION

For GPS/INS system integration, synchronization must be provided between GPS and INS systems, to make it possible to compare the reading data of both systems.

Predicting or extrapolating the missing reading data of the GPS to be compatible with those of the INS data can accomplish to solve the difference in sampling rate problem between the two systems.

Different strategies are used to predict the GPS data (data at intermediate times). The third strategy was more accurate from the first and second strategies but they are the key for the third accurate strategy. So, they will be illustrated in next subsections to show the effect of using different strategies on the extrapolation for more investigation and research.

Figure 3 shows the flowchart for the general extrapolation process of GPS data prediction. The adaptive neuro fuzzy inference system is proposed as a core to solve the difference in data rate between GPS and INS (i.e to predict the GPS data at intermediate times). The training phase was carried out after initializing all position and velocity networks with learning rate = 0.6, number of rules = 60, learning parameters (c =[-2,2],b =[-4,4],a =[0.2 ,3]), number of epochs = 1000. Utilizing the learned

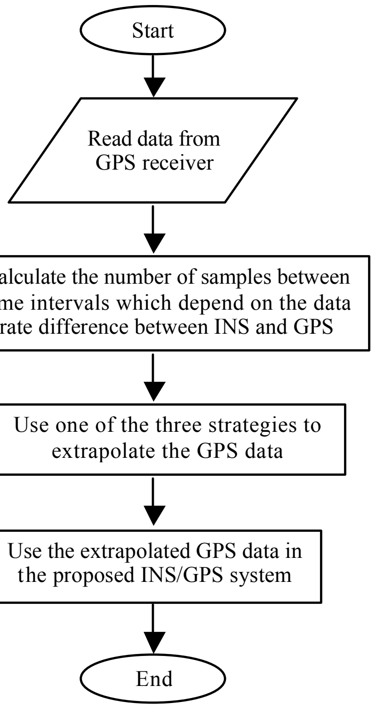

Fig. 3: General extrapolation process of GPS data prediction

parameters (c, b, a), the following three strategies were used to extrapolate the GPS data as follows:

First strategy: The first strategy supposes that the GPS and INS provide reading data each 1 and 0.1 second respectively. It assume that we have the first two reading data at time 1 and 2 second of the GPS and the intelligent predictor will be used to extrapolate the GPS data at time {2.1, 2.2,….,2.9} seconds then the reading data at time 3 second will be already available and we do not need to process it to be extrapolated further more it can be assigned from INS data. So, the reading data at time 2, and 3 seconds was available and the ANFIS will be extrapolate the GPS data at time {3.1, 3.2,…., 3.9} seconds and continue this processing until reach the end of the number of samples.

It must be noticed that we extrapolate the reading from time (2.1 to 2.9) seconds depending on reading data at time (1and 2) seconds which are available. Figure 4 shows the first extrapolation strategy of GPS data.

Second strategy: Since the INS reading data is delivered every 0.1 second then after 10 reading of INS data was received the estimation process was accomplished to estimate the reading data at time 2.1 second depending on two previous reading data at times (1.9 and 2) seconds and after the processes to estimate the reading data at time 2.1 second was completed, then we use the data at time 2, and 2.1 second to estimate the data at time "2.2 second" and so on (notice that the data at time "2 second" will be used with the data obtained from the estimation process at time "2.1 second"). Figure 5 shows the second extrapolation strategy of GPS data.

Third strategy: The main idea is the same as second strategy but to achieve more accurate result some reading data from the INS system will be assigned in the estimation process to reduce the oscillation, which obtained from the estimation process. So, the reading data in integer times such as (2, 3, 4, …, etc) seconds, will be assigned instead of estimated them which produce more accurate estimated trajectory.

Table 1 shows the performance of the results obtained from the three strategies. Figure 6 compares between the true trajectory and the extrapolated trajectories resulted from implementing the three strategies for position and velocity components. Figure 7 shows a comparison between the errors of the three strategies for all components.

The mean square error can be calculated using,

$$MSE = \sum_{i=1}^{n} E_{model}{}^{2} \tag{6}$$

Where

$$E_{model} = E_{real} - E_{predicted} \tag{7}$$

Also the standard deviation can be calculated using,

$$\text{Standard deviation} = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{1/2} \tag{8}$$

where

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{9}$$

and n is the number of elements in the sample.

RESULTS AND CONCLUSION

This paper introduced a new method for solving the difference in data rate between GPS and INS system based on ANFIS. From the results obtained in this paper we can conclude that the ANFIS gives a better solution to the problem of difference in sampling rates in a short time interval. In general, third strategy produces better results, in terms of the standard deviation and means values, than the other two strategies since it uses the true trajectory data of the nearest samples to the extrapolated one. The three strategies give better

Table 1: Performance of the intelligent predictor based ANFIS

	Position (m)			Velocity (m/sec)		
	X-Axis	Y-Axis	Z-Axis	North	East	Down
First strategy						
MSE	8.5543e-06	2.4583e-05	2.3569e-05	0.8882	0.0043	0.0055
STD	18.2224	11.1012	10.4952	5.5438	4.5569	5.6643
Mean	22.8661	11.3222	16.4431	-14.5590	6.5511	-7.9088
Elapsed time (s)	0.5420	0.5420	0.5420	0.3370	0.3380	0.5232
Prediction time (s)	8.3359e-04	6.5539e-04	6.5559e-04	6.5665e-04	6.5547e-04	6.5540e-04
Second strategy						
MSE	5.3342e-07	4.8876e-05	8.2237e-06	0.6613	0.0055	0.0022
STD	14.5562	12.6679	8.4442	4.5334	3.4556	5.8870
Mean	-22.4456	-13.6634	-18.5573	-8.0586	1.9011	-6.0091
Elapsed time (s)	0.6770	0.4450	0.4970	0.5570	0.5560	0.5590
Prediction time (s)	10.998e-04	8.8112e-04	11.029e-04	8.7765e-04	8.6612e-04	9.9901e-04
Third strategy						
MSE	3.9517e-06	1.9963e-06	4.8899e-07	0.0081	0.0067	0.0077
STD	3.0011	3.0531	5.0109	0.2047	0.2008	3.0013
Mean	8.2139	-4.0206	5.9811	-2.9635	3.9761	-1.9966
Elapsed time (s)	0.4431	0.5330	0.5340	0.5330	0.5330	0.5330
Prediction time (s)	6.9912e-04	8.9875e-04	8.9985e-04	8.0015e-04	8.0015e-04	8.0015e-04

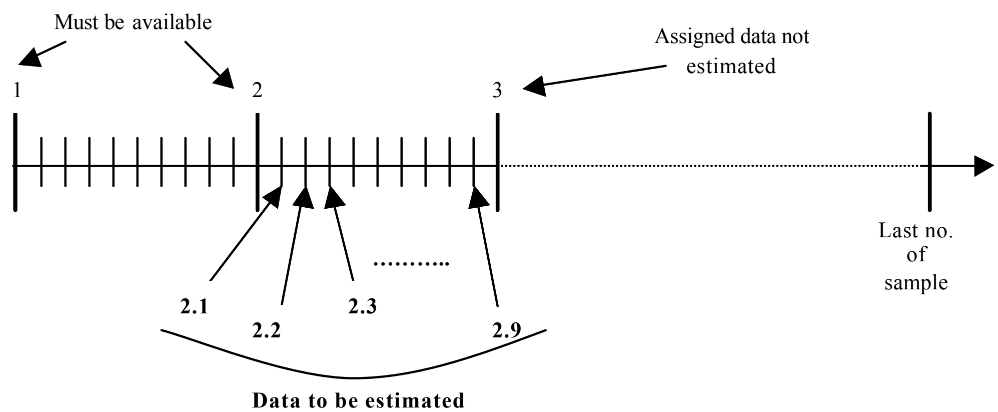

Fig. 4: First strategy for GPS data extrapolation

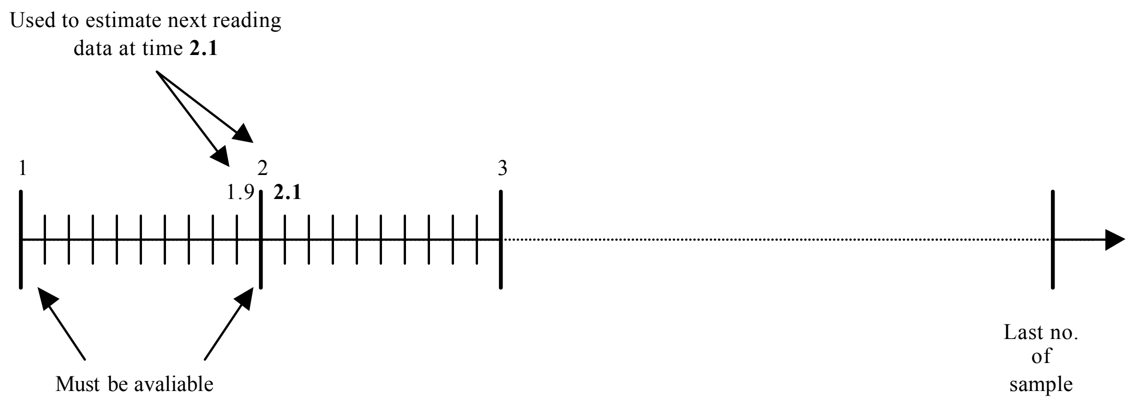

Fig. 5: Second strategy for GPS data extrapolation

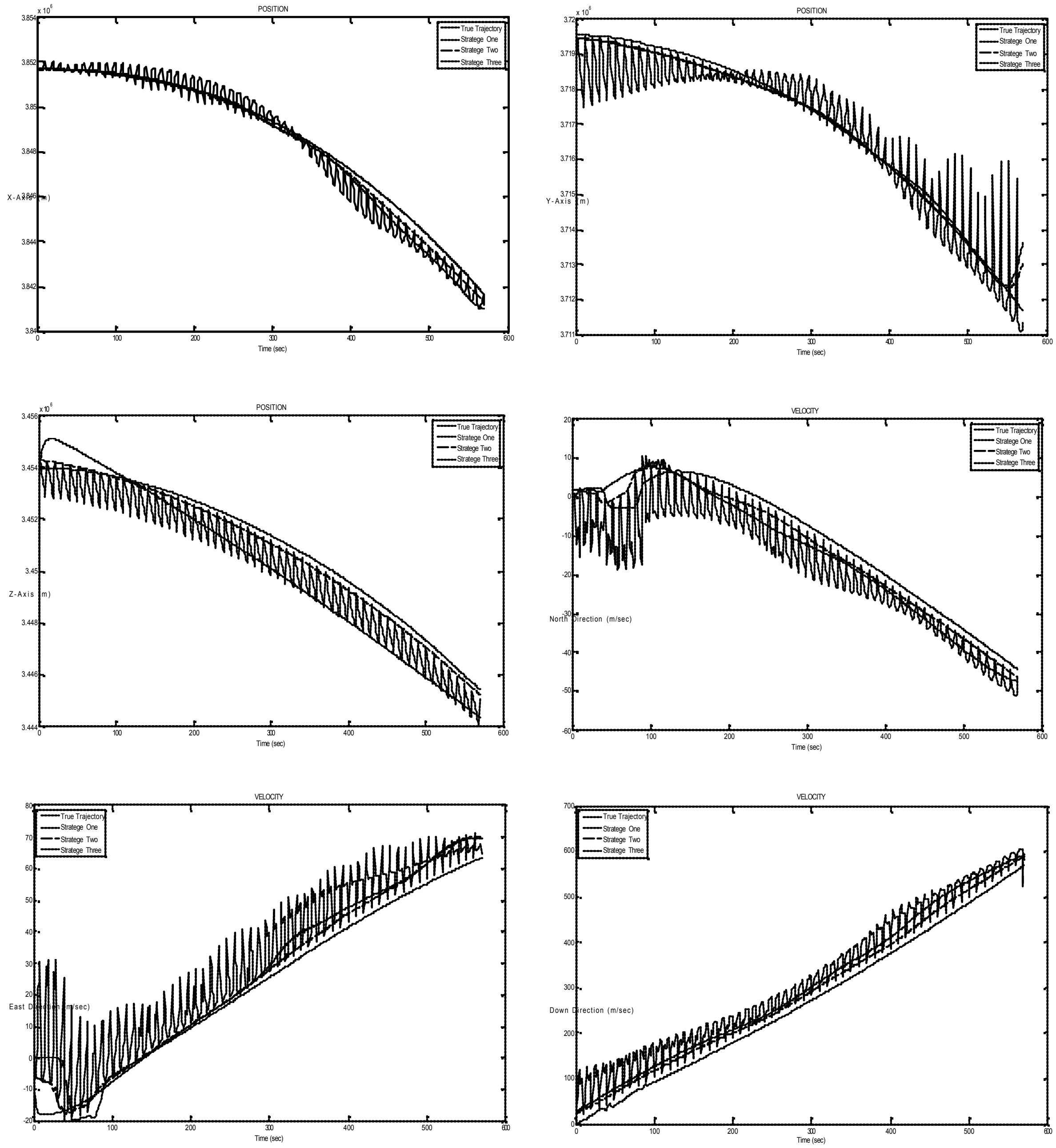

Fig. 6: Comparison between the true and predicted trajectories using three strategies for position and velocity in all directions

results in extrapolating the velocity components than the position components.

It can be said that ANFIS require prior knowledge of the trajectory. To solve this problem a database must be built for the selected trajectories to be used (i.e. roads in the city for the moving vehicle). On the other hand, the ANFIS has an advantage over other algorithms such as Neural Network in terms of the capacity required in memory to implement the prediction algorithms regarding to the programs that will be used. However, the third strategy provide acceptable positions and velocity accuracies compared to the other strategies it is also possible to enhance its accuracies by optimizing the internal system parameters using evolutionary techniques such as Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) and other optimization techniques as a future development.

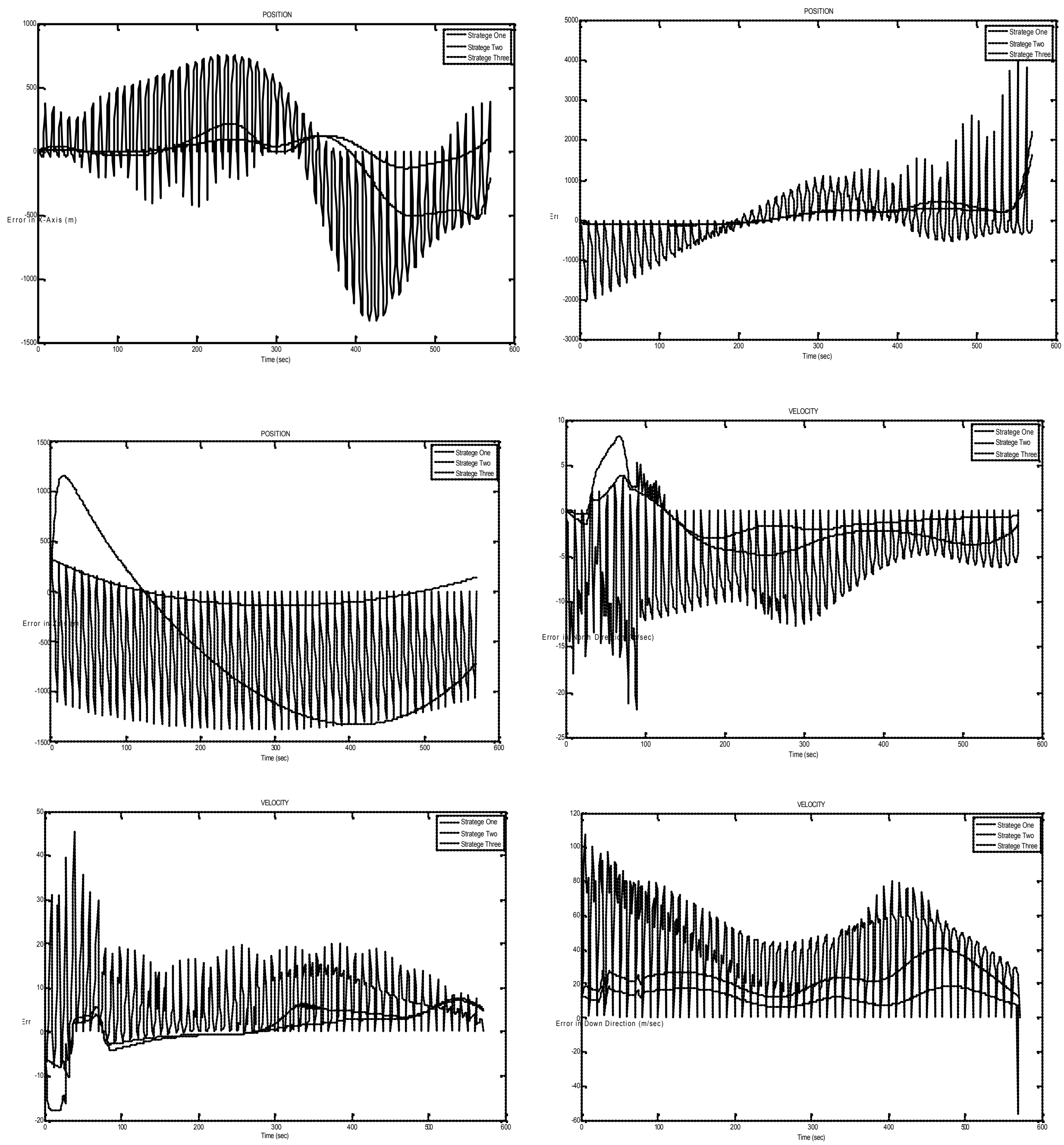

Fig. 7: Resulted Error evaluated using three strategies for position and velocity in all directions

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