ADAPTIVE FUZZY SYSTEM FOR GPS DATA PREDICTION

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Abstract

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.

So that, the combination of GPS and INS has become increasingly common in the past few years, because the characteristics of GPS and INS are complementary.

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.

Keywords: GPS, INS, ANFIS, Navigation system.

الخلاصة

بمرور الزمن ، أنظمة الملاحة بعزم القصور الذاتي تنحرف عن الانحياز المسبق أو أن الانحياز الاولي قد يتغير بسبب حركة المركبة ،مع النقل غير تام للانحياز والسرعة للملاح . كذلك قد لايكون هناك وقت كافي لعمل أنحياز دقيق . وفي هذه الحالة فأن الملاح يستطيع الاستفادة من الانظمة المساعدة كمنظومة تحديث الموقع العالمي .

لذلك فأن الجمع بين منظومة الملاحة بعزم القصور الذاتي ومنظومة تحديد الموقع العالمي بدأ يزداد في السنوات القليلة الماضية ، بسبب الخواص المتناقضة لكلا من منظومة ملاحة بعزم القصور الذاتي ونظام تحديد الموقع العالمي

التكامل بين منظومة تحديد الموقع العالمي ومنظومة الملاحة بعزم القصور الذاتي يقود الى الحصول على ملاحة دقيقة بتجاوز كل من عيوب المنظومتين . ولجعل هذا التكامل ممكنا فأن الفرق بين منظومة تحديد موقع العالمي ومنظومة الملاحة بعزم القصور الذاتي بالنسبة لسرعة اعطاء معلومات يجب ان تحل قبل ان يعمل اي تكامل بينهما كما ينبغي .

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1. 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. 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].

There are many GPS applications, including air, land, and marine navigation, precision agriculture, surveying, and precise timing, and there are different receivers specific to each application [3].

2. Problem Statement

The INS and GPS are difference 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 articles overcomes this problem by choosing the GPS and INS systems with the same sampling rate as in [4], or can extrapolate the GPS data using neural network to be matched with the INS data to make the integration possible as done in [5],
Or Between instants as in [6].

3. Adaptive Fuzzy Systems (AFS)

AFS is an adaptive network based on fuzzy inference systems. It
combines fuzzy logic and neural networks to facilitate the hybrid learning procedure. AFS architecture consists of five consecutive layers as illustrated in Figure 1 [7].

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.

AFS 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 AFS process starts with the clustering data set at the input layer and describing both the feed forward and backward propagation procedures.

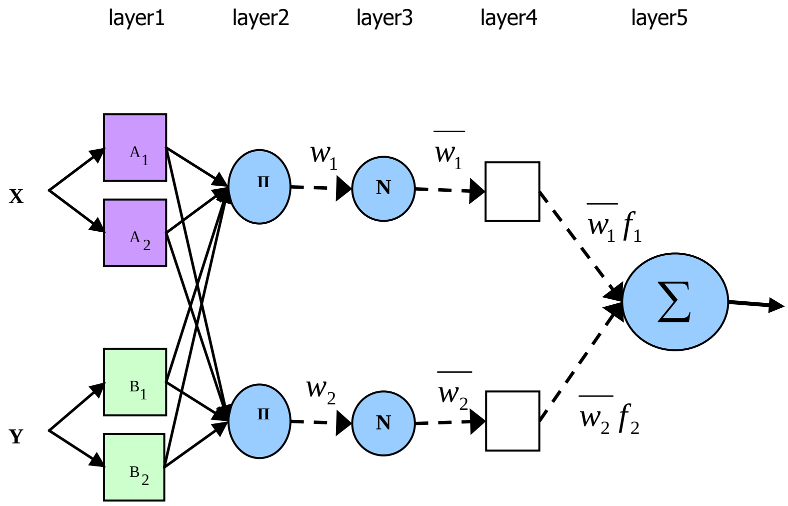

Figure (1): Schematic of the Neuro-fuzzy model

2.1 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 [8]. 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 [8]:

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

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 neighbourhood, 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 [8]:

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

…(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 [7]. The following step to the clustering the input data set is the fuzzification of this data set.

2.2 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 Figure 2. These antecedent parameters highly affect the output of each function and hence they shall be updated in order to provide the desired input-outputrelationship.

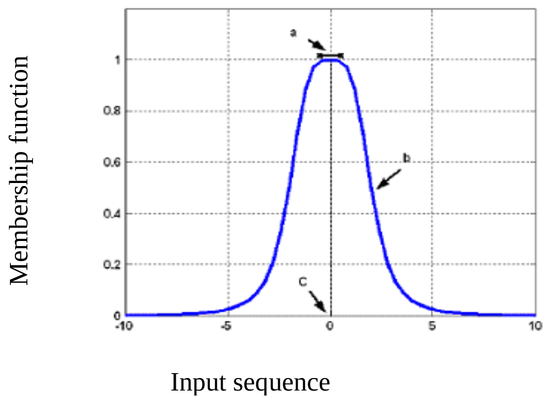

Figure (2): Generalized bell membership function

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 bellshape MFs determine the width, spread and center of the MF respectively as in the following expression.

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

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

2.3 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.

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

where are $\{p_i, q_i, r_i\}$ the linear unknown consequent parameters estimated using the method of the least squares [9].

2.4 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 [10]. This method is the most frequently used in nonlinear optimization technique due to its simplicity. The steepest descent formula is presented as follow:

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

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 η not be stable. The AFS algorithm is implemented using MATLAB environment. The algorithm allows changing the initial step size during training based on the error measure of the AFS prediction.

In summary, the paramount advantage of AFS 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.

3. The Proposed AFS for GPS prediction

For GPS/INS system integration, synchronization must be provided between them, 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). One of them was more accurate from the previous two 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.

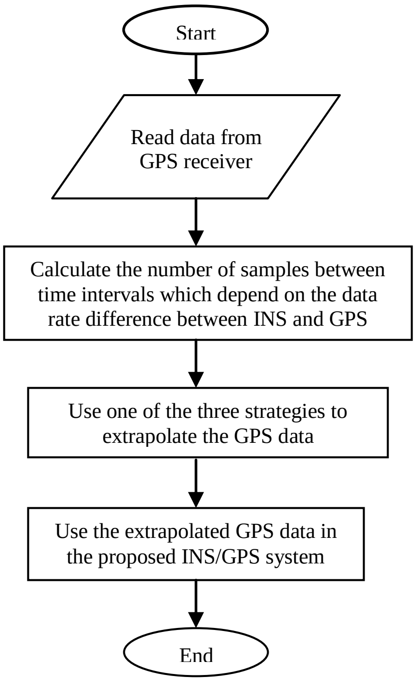

Figure (3): General extrapolation process of GPS prediction

The data used in this work was generated from six degree of freedom (6DOF) missile simulation based in matlab so, the results may be differing if real data used (i.e vehicle trajectory instead of missile).

The adaptive neuro fuzzy inference system is proposed as a core method 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 = 40, learning parameters (c =[-1,1],b =[-2,2],a =[0.01,3.01]), number of epochs = 1000. Utilizing the learned parameters (c, b, a), the following three strategies were used to extrapolate the GPS data as follows:

3.1 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 AFS 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 don't 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 AFS will be extrapolate the GPS data at time {3.1, 3.2,…., 3.9} seconds and continue the processing until reach the end of 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 (1, and 2) seconds who are available. Figure (4) shows the extrapolation strategy of GPS data.

3.2 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 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 result from the estimation process at time 2.1 second). Figure (5) shows the extrapolation strategy of GPS data.

3.3 Third Strategy

The main idea is the same as second strategy but to accomplish 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. will be assigned instead of estimated it which produce more accurate estimated trajectory.
Table (1) shows the results obtained from the three strategies. Figure (6) compares between the true trajectory and the extrapolated trajectory 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,

$$MSE = \sum_{i=1}^{n} E_{\mathrm{model}_i}{}^2$$

Where

$$E_{\mathrm{model}} = E_{real} - E_{predicted};$$

Also the standard deviation can be calculated using,

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

Where,

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

And n is the number of elements in the sample

4. Conclusions

From the results, the following conclusions can be drawn:

1. The AFS gives the solution to the problem of difference in sampling rates in a short time interval.
2. 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.
3. The three strategies give better results in extrapolating the velocity components than the position components.

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4. It can be said that AFS 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

5. The other hand, the AFS has an advantage over other algorithms such as Neural Network in terms of the capacity required in memory to implement the programs.

5. Refernces

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Table (1): Performance of GPS Extrapolation using AFS.

		Position			Velocity		
		X-axis (m)	Y-axis (m)	Z-axis (m)	North (m/s)	East (m/s)	Down (m/s)
First Strategy	MSE	9.6207e-006	1.1786e-005	1.2299e-005	0.9082	0.0023	0.0049
	STD	17.2244	12.1082	14.4952	5.3266	3.9506	4.0437
	Mean	20.9971	-14.3932	18.8015	-12.4358	5.2623	-8.4992
	Elapsed Time (s)	0.4220	0.4220	0.4220	0.4370	0.4380	0.4060
	Prediction Time (s)	7.2759e-004	7.2759e-004	7.2759e-004	7.5345e-004	7.5517e-004	7.0000e-004
Second Strategy	MSE	5.256e-007	3.4556e-005	7.9257e-006	0.8953	0.0056	0.0031
	STD	13.9602	11.3379	9.3942	3.5444	2.5476	4.3600
	Mean	-24.7533	-10.6734	-20.7473	-7.5586	2.1071	-5.7839
	Elapsed Time (s)	0.5620	0.4530	0.5160	0.4370	0.4060	0.4690
	Prediction Time (s)	9.8596e-004	7.9474e-004	9.0526e-004	7.6667e-004	7.1228e-004	8.2281e-004
Third Strategy	MSE	4.2587e-006	2.2563e-006	3.8757e-007	0.0078	0.0063	0.0085
	STD	2.9012	2.8531	4.9449	0.1647	0.1788	2.8063
	Mean	7.5334	-3.7204	5.7194	-3.1635	4.2271	-2.4626
	Elapsed Time (s)	0.4370	0.4220	0.5320	0.4220	0.4220	0.4220
	Prediction Time (s)	7.6667e-004	7.4035e-004	9.3333e-004	7.4035e-004	7.4035e-004	7.4035e-004

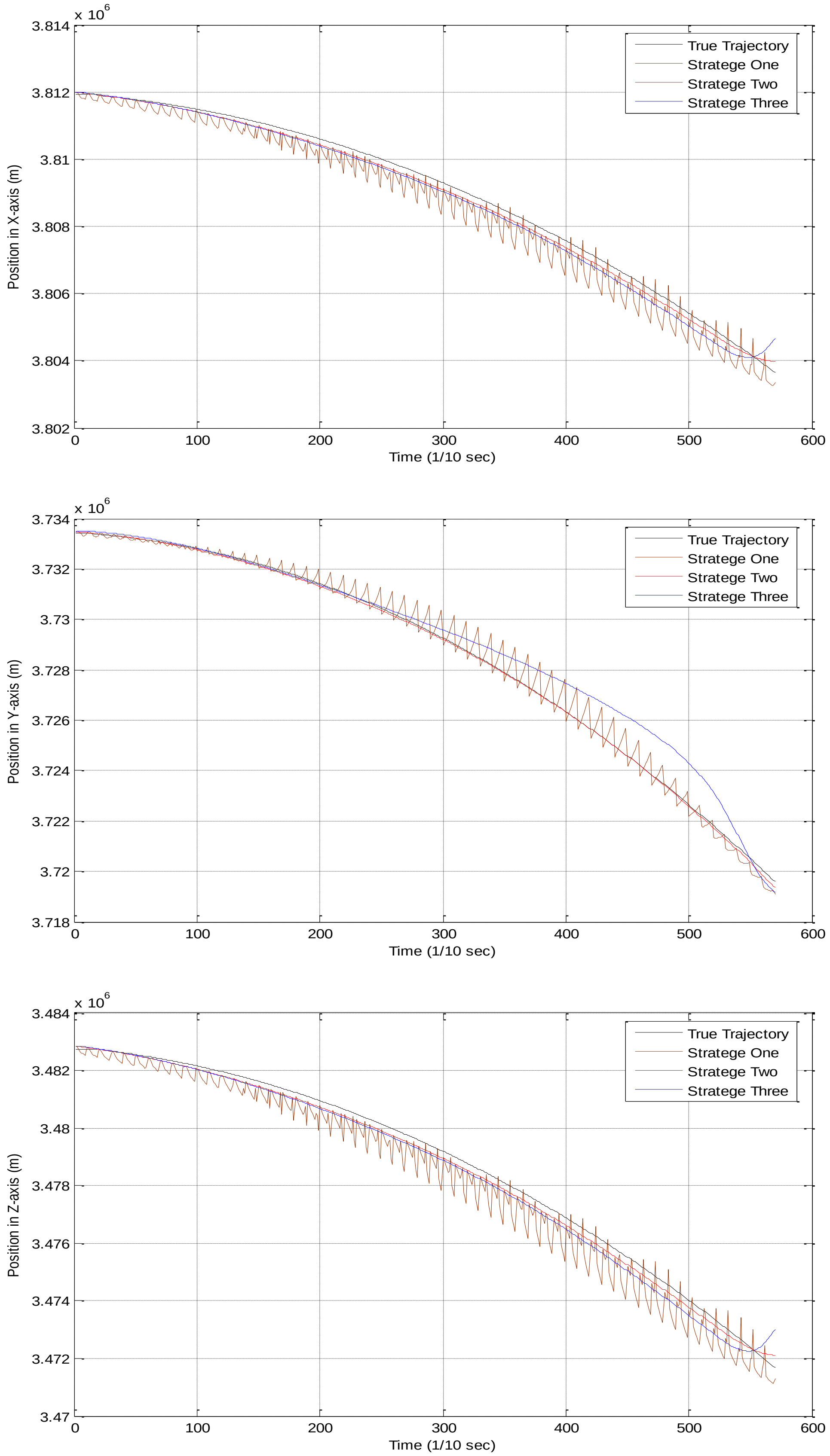


Figure (6): Comparison between the True and Predicted trajectories using three strategies for Position and Velocity in all directions.

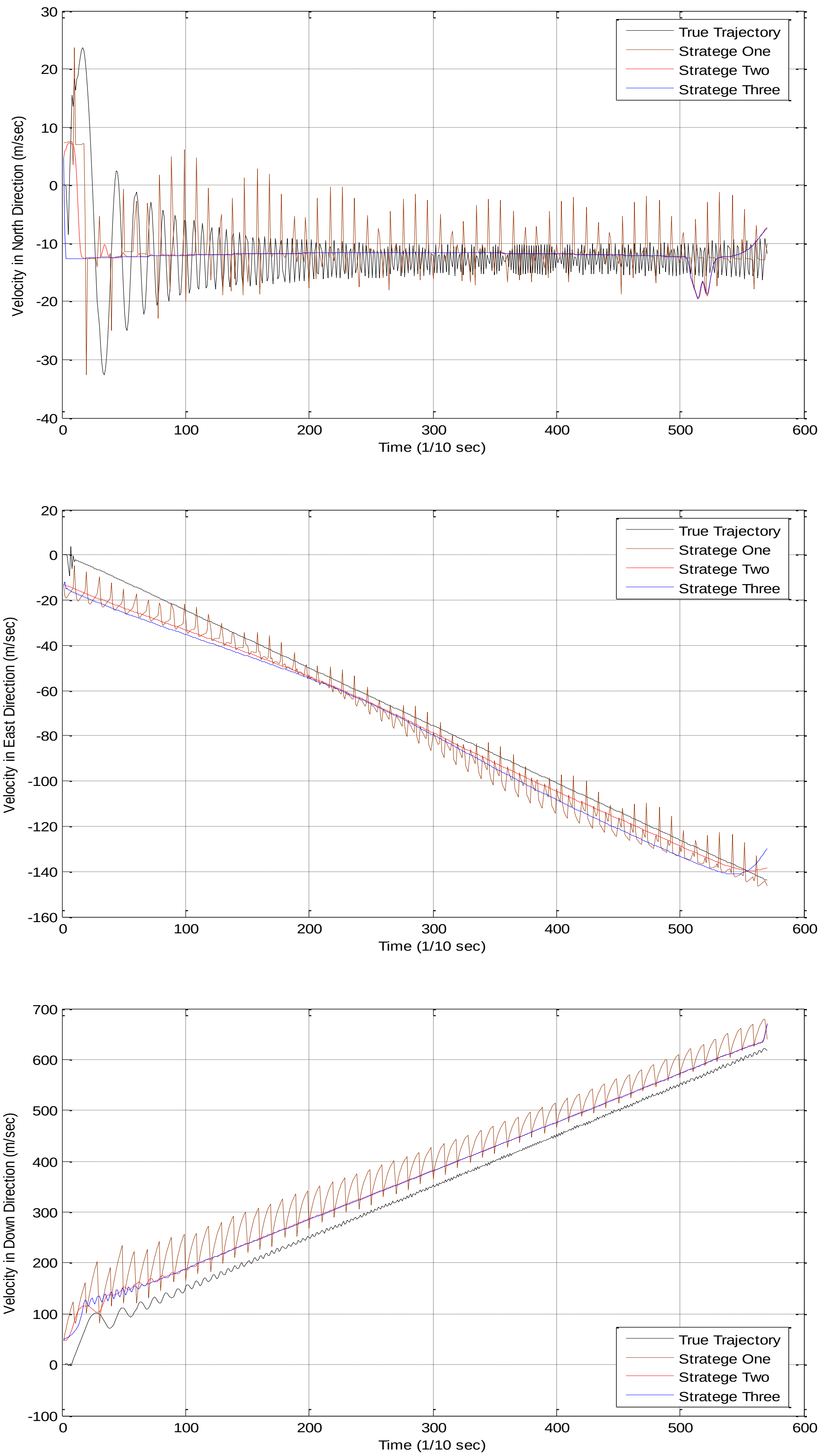


Figure (6): Continued.

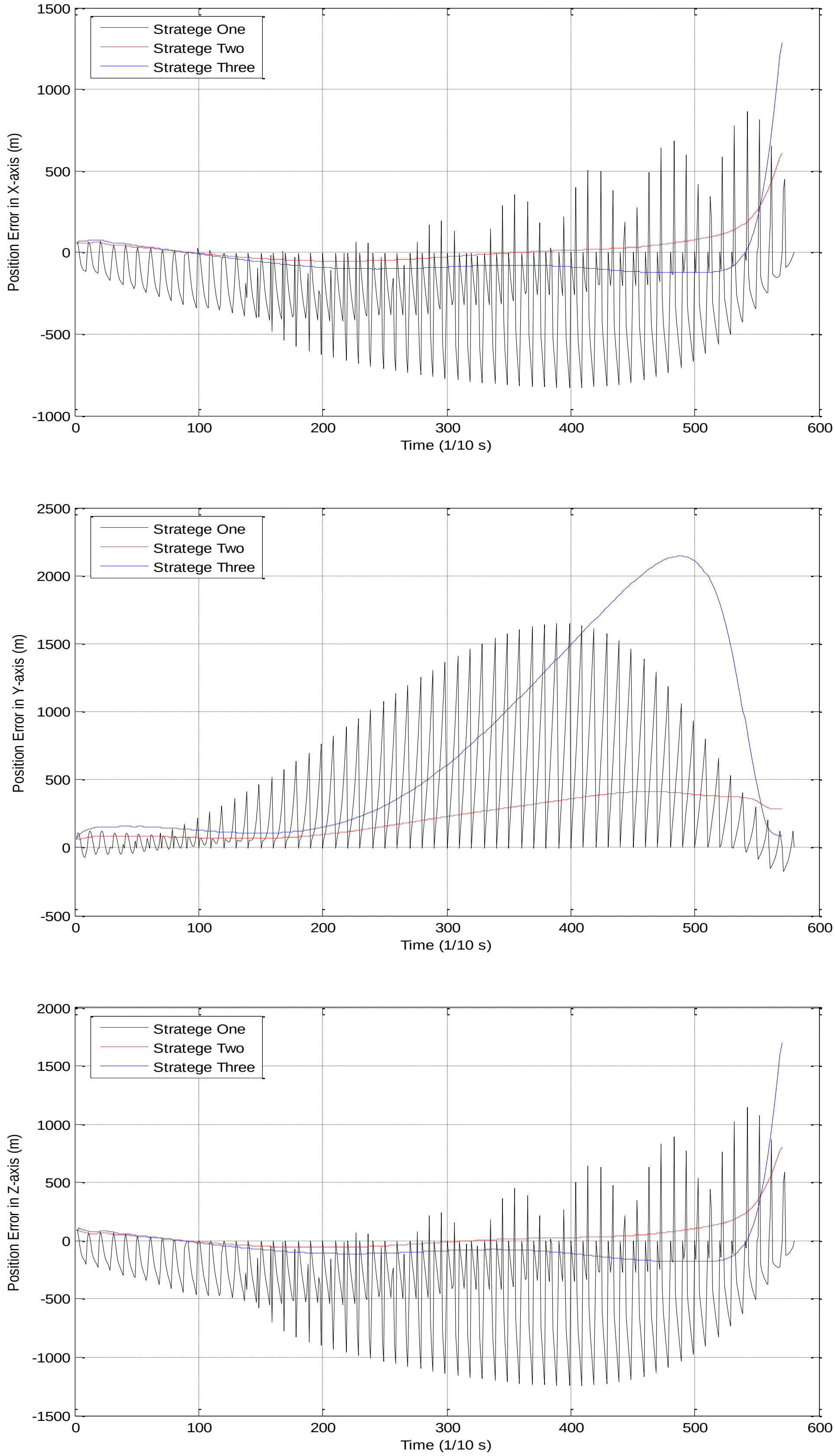


Figure (7): Resulted Error evaluated using three strategies for position and velocity in all directions.

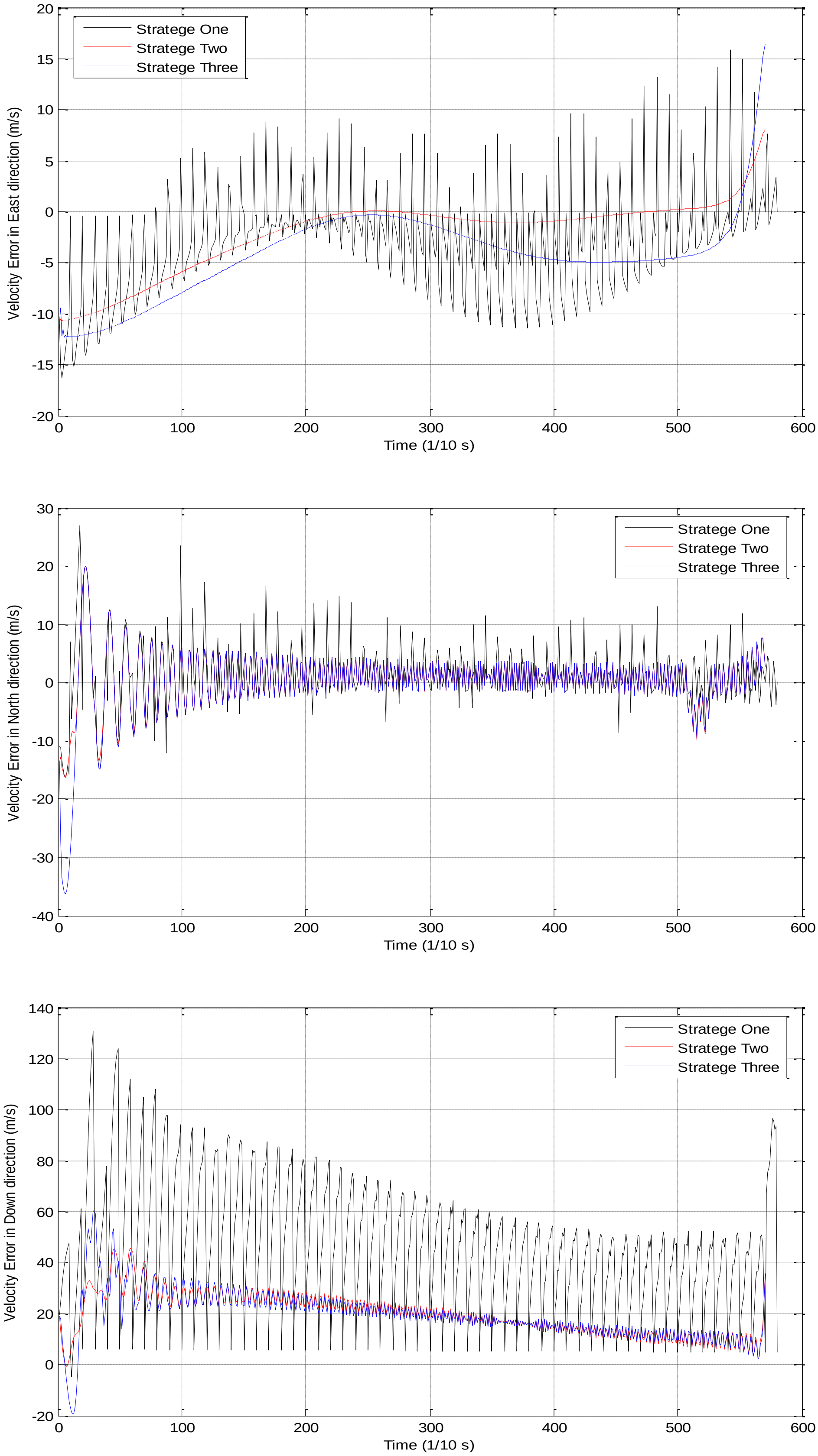
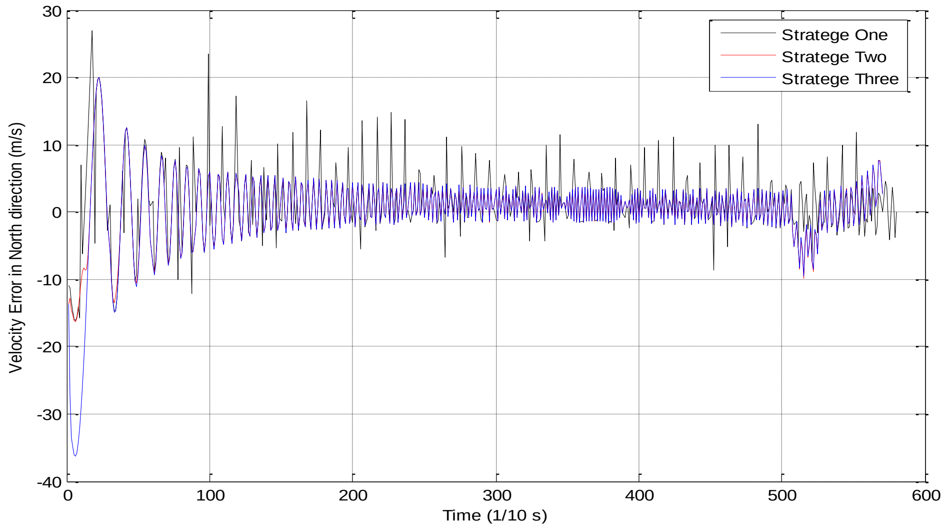
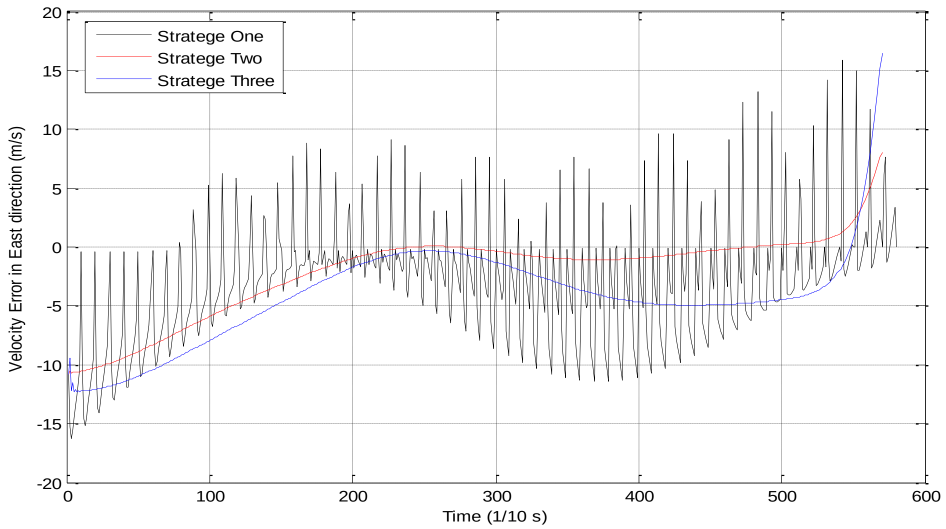
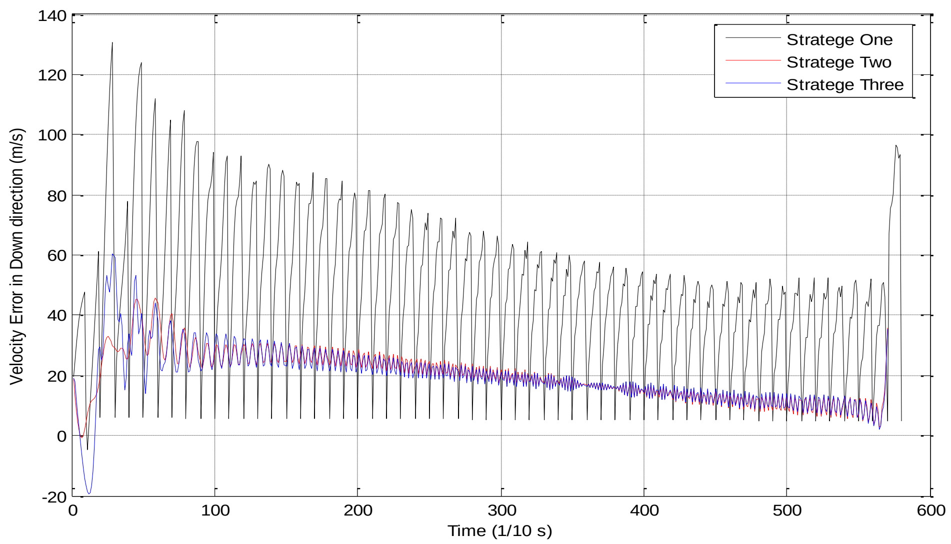


Figure (7): Continued.


Velocity Error in North direction (m/s)
Time (1/10 s)
Stratege One
Stratege Two
Stratege Three
30
20
10
0
-10
-20
-30
-40
0
100
200
300
400
500
600


Velocity Error in East direction (m/s)
Time (1/10 s)
Stratege One
Stratege Two
Stratege Three
20
15
10
5
0
-5
-10
-15
-20
0
100
200
300
400
500
600


Velocity Error in Down direction (m/s)
Time (1/10 s)
Stratege One
Stratege Two
Stratege Three
140
120
100
80
60
40
20
0
-20
0
100
200
300
400
500
600