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Full Length Research Paper

A novel intelligent predictor for low-rate global positioning system (GPS) system

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Global positioning system (GPS) is the most common instrument utilized for navigational purpose. Unfortunately these satellite signals may get lost due to signal blockage. On the other hand, inertial navigation systems (INSs) can address this problem and overcome the non-availability of GPS signals for a short period of time due to the inherent sensors errors. In such case, INSs can benefit from aiding such as GPS. The difference in sampling rate between the GPS and INS must be overcome to realize the integration of the two systems. In general, Kalman filter (KF) is used to predict GPS data in order to integrate signals from high data rate systems, like INSs, with GPS that have low data rate. However, KF is usually criticized for working under predefined linear dynamic error models. In this paper, adaptive neuro fuzzy inference system (ANFIS) trained using genetic algorithm (GA) was adopted to predict the mislaid reading data for GPS to be synchronized with those of INS data. 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 square error.

Key words: Global positioning system, inertial navigation system, adaptive neuro fuzzy inference system, genetic algorithm.

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 (Farrell and Barth, 1999).

Strapdown inertial navigation system (SDINS) technologies are based on the principle of integrating specific forces and rates measured by accelerometers and rate gyros of an inertial measurement unit (IMU) fixed on the moving body (David and John, 2004). On the other hand, the GPS relies on the technique of comparing 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 (Wellenhof et al., 2001; Mohinder et al., 2001).

The combination of GPS and INS has become increasingly common in the past few years, because the characteristics of GPS and INS are complementary. GPS and INS both can be used for wide range of navigation functions. Each has its strengths and weaknesses as illustrated in Table 1.

This paper aims to provide a high supremacy method to combined different data rate GPS with INS data without sacrificing performance even if using low cost inertial sensors. Generally INS produces a high data rate, compared to the GPS receiver (approximately > 10 Hz for INS systems and 1 Hz or more for Normal GPS). Therefore, there is gap between these two systems reading data. Some researchers overcomes this difficulties by choosing the GPS and INS systems with the same sampling rate when integrating the GPS and INS systems (Shin and El-Sheimy, 2002), while other researcher alter the INS mechanization so both the INS and GPS data are synchronized to follow the GPS time tag (Noureldin et al.,

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Table 1. Comparison of INS and GPS systems (Chiang et al., 2008)

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

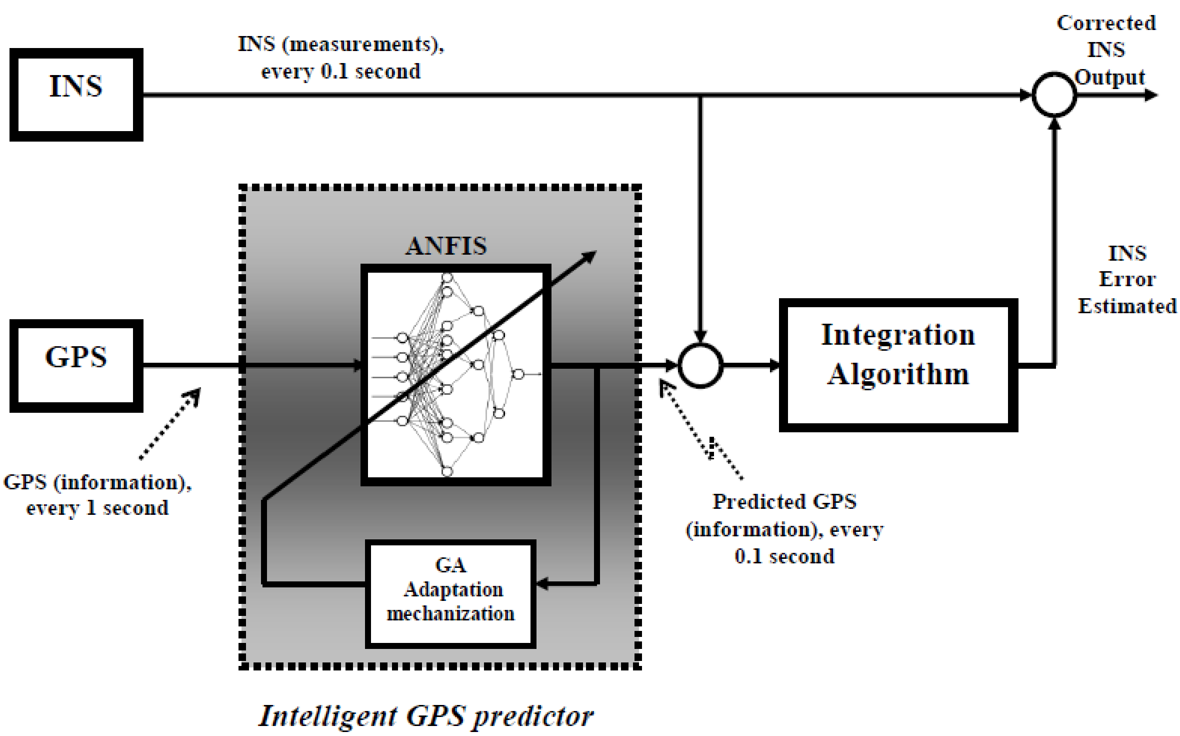


Figure 1. Main structure for GPS/INS integration showing the proposed Intelligent GPS predictor.

2007; Noureldin et al., 2009; Xu et al., 2010; Chiang et al., 2008), or using Kalman filter to predict the sampling between instants (Mayhew, 1999; Mao et al., 2007; Nassar and El-Sheimy, 2006). Typically, INS has been widely used as reference system, which provides navigation solutions such as position, velocity, and attitude. Although GPS measurements are used to update and correct the INS solution and approximate the error states. Also, Kalman filter has been widely used to predict the GPS sampling data between instant. Hence, Mohamed and Schwarz (1999) use a decentralized filtering technique, where two Kalman filters are formulated. One is the GPS filter that deals with GPS data only to predict the missing GPS data, while the second filter is the INS filter to estimate the error states for position, velocity, and attitude. Moreover, these filters can work independently to handle the GPS and INS measurements together. However, there are several significant drawbacks related to Kalman filter such as the necessity for *a priori* information of the system and measurement covariance matrices for each new sensor that could be difficult to accurately verify. Another typical problem related to Kalman filtering is weak observability of some of the error states that may lead to unstable estimate of another error states (Al-Faiz and Ismaeel, 2005; Lorinda and Aboelmagd, 2006; Vanicek and Omerbasic, 1999). While this paper is different in handling the deficiency in navigation systems utilizing the adaptive neuro-fuzzy inference system by using the GPS data outputs as inputs to the proposed intelligent predictor to predict the GPS data between instants as shown in the main structure of the GPS/INS integration in Figure 1.

In general, utilizing artificial intelligence (AI) presents numerous compensations if evaluated against Kalman

Table 2. Comparison between AI and Kalman filtering GPS/INS integration system (Nguyen, 2009).

	Kalman filtering	AI
Model dependence	Mathematical model is needed (deterministic model + stochastic model)	Empirical and adaptive model
A priori Knowledge	Required the covariance of INS and GPS data (mainly Q and R matrix)	Not required
Sensor dependence	Re-design of Kalman Filter parameters is needed for different systems	An adaptable, platform and system independent algorithm
Linearity	Linear processing	Nonlinear processing
Design time	Long	Short

filtering (KF). A comparison between artificial intelligence and kalman filtering techniques is illustrated in Table 2.

It is widely anticipated that intelligent predictor should be used with different types of sensors. However, from the literature it is evident that there is a lack of research which focuses on these issues. Also, many published work in the GPS/INS integration field suggest solving the difference in data rate problem as a future work (Mayhew, 1999; Nguyen, 2009). The proposed solution provide flexibility to integrate different rate systems, such as GPS and INS. ANFIS trained by genetic algorithm (GA) is adopted in this paper to predict the intermediate GPS data between instants.

This paper is organized as follows: in section 2 we describe the adaptive neuro fuzzy inference system structure by illustrating its five consequent layers. Section 3 presents the Genetic Algorithm used to optimize the learning parameters for the intelligent predictor. The suggested integration structure is explained in section 4. While three strategies to predict the missing GPS data based on ANFIS are discussed in section 5. Finally, results and discussion are given in section 5.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM STRUCTURE

Adaptive fuzzy system was selected for implementing the intelligent predictor due to several reasons:

(1) Its swift ability of input and output mapping, therefore, well-compatible for mapping the GPS data as input to predict missing GPS data as outputs.

(2) The proposed model-less system requires no prior information of the GPS sensor characteristics and simplifies the integration of different type of system.

(3) Adaptive fuzzy system consists of a fixed simple structure with compact computation resources leading to real time implementation.

Consequently, ANFIS is simplest compared to other artificial intelligence such as neural network that require to find out the optimal number of hidden layer and the number of neurons in each layer (Al-Faiz and Ismaeel, 2005; Jeffrey and Ben, 2004).

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

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

where M is the number of fuzzy IF-THEN rules, while yj is the center of fuzzy set fj, that is, a point in the universe of discourse V at which μFi(y) achieves its highest value, and μFi(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 modelling and control systems. Hence, Equation (1) becomes:

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

where n is the number of input linguistic variables.

In order to develop training algorithm for this fuzzy logic system, the functional form of μFi(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 genetic algorithm for

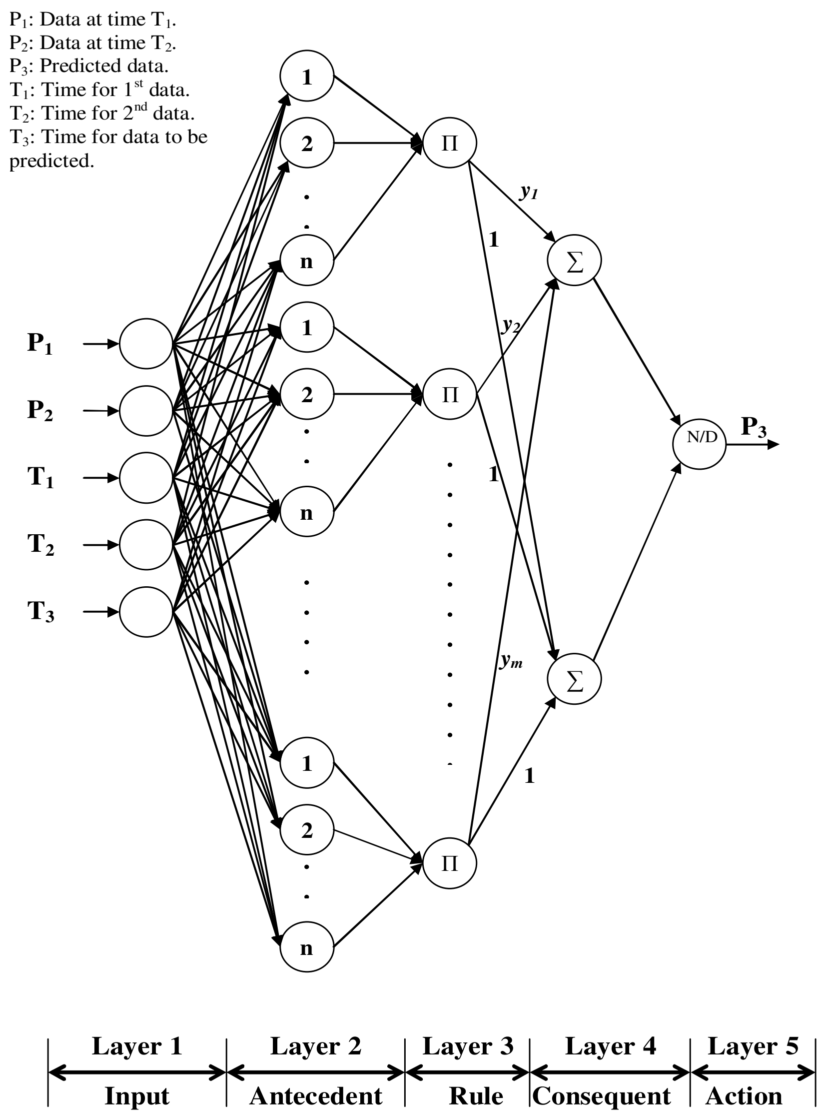


Figure 2. The Architecture of an ANFIS network for predicting GPS data.

optimizing the ANFIS parameters, i.e. the membership function can be given by the following equation:

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

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

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

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

where: f(x): fuzzy logic system output, which represent a function to n input variables x. x_i : Input variable in the input universe of discourse. y_j :Center of fuzzy set F_j, which is, a point in the universe of discourse V when membership function ($\mu_{Fj}(y)$ achieves its maximum value, and $\mu_{Fj}(y)$ is given by a product inference engine. M, N:number of fuzzy rules and input variables respectively. m_i, σ_i: Center and width of the bell-shaped function of the ith input variable, respectively.

This equation represents a fuzzy logic system with center average defuzzifier, product inference rule, singleton fuzzifier, and bell shaped membership function (Saraireh et al., 1999). Wang (1994) shows that this fuzzy logic system is universal approximator (that is, 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 expose 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.

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 ith node in layer I. 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:

(1) Input layer: The unique function of these nodes in this layer is just transmitting their input values directly to Layer 2:

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

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

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 Layer 2 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 (that is, 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 represents the numerator and denominator of Equation (4) respectively.

(5) Action layer: Only one node exits in this layer. Here the actual output would be pumped out the net:

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

GENETIC ALGORITHM BASED STRUCTURE OPTIMIZATION AND PARAMETERS LEARNING

GA is an optimizing algorithm based on the mechanics of natural selection and natural genetics. The searching process is comparable with the natural evolution of biological creatures in which successive generations of organisms are given birth and raised until they themselves are able to breed. GAs has revealed their robustness in the field of optimization, especially when the mathematical model of the optimization problem is quite complicated or not well defined (Saggiani et al., 2004; Taghi et al., 2010).

ANFIS is an adaptive network based on fuzzy inference systems. The training and optimization of the ANFIS parameters is one of the major problems. ANFIS architecture consists of five consecutive layers as illustrated in Figure 2. Different interpretations for the fuzzy IF-THEN rules result in different mappings of the fuzzy inference engine; also there are different types of fuzzifier and defuzzifier. Several combinations of the fuzzy inference engine, fuzzifier, and defuzzifier may comprise useful fuzzy logic system can be represented as a feed forward network, and then genetic algorithm

Table 3. Continuous genetic algorithm parameters settings.

Parameters	Setting
Max. generation	100
Population size	10
Selection type	Hybrid selection method
Crossover	One point crossover
Mutation	Replace the mutated gene with random number
Crossover probability (P_c)	0.8
Mutation probability (P_m)	0.02
Gene range	[-1, 1]
Number of genes in chromosome	110

The training of the ANFIS network in the antecedent part is more difficult than the consequent part, because in gradient descent (GD) method it must go through all layers which increase the required calculation. The GD that is used in the antecedent part may lead to a local minimum. Therefore, we propose GA as an optimization method which can optimize the antecedent part.

Equation (4) represents a fuzzy logic system with centre average defuzzifier, product inference rule, non-singleton fuzzifier, and bell-shaped membership function.

In this paper, the MatLab software has been used for the implementation of a real-coded GA, specifically developed in order to optimize and train the conceptual intelligent predictor, rather than using the available genetic and fuzzy logic toolboxes in MatLab used in reference (Hassanain et al., 2004).

In addition to, Equation (4) can be implemented on a forward neural network (FNN) and based on the GA optimization technique, the goal is to determine a fuzzy logic f(x), in the form of Equation (4), which minimizes the objective function:

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

where P is the number of outputs and d_j (k) is the jth desired output at time k. According to Equation (14) if the number of rules is M, then the problem becomes training the parameters y_j, m_{ij}, and σ_{ij} such that E(k) is minimized. Then, the chromosome representation for the prediction system can be summarized as: 10 genes for y_j, and 50 genes for both m_{ij}, and σ_{ij}. Therefore, a total of 110 genes are required to represent each chromosome in the GA for training the predictor system. And it must be mentioned that the range for the initial population of these parameters is [-1,1]. Table 3 shows the parameters used for initializing the GA.

Real coded genetic algorithm

The real-coded GA requires the following operators:

Hybrid selection method

After the initial population a hybrid selection method which is incarnation of roulette wheel and deterministic selection. This selection method ensures that the new population will contain chromosomes with better fitness values than the worst individual in the old population. This permutation will reduce the iteration required for learning process while ensuring good guidance in a complex and nonlinear search space (Al-Said, 2000).

Elitism

In this procedure the best parents from the old population will be copied into the next generation without performing any operators to increase the probability of obtaining best fitness values and preventing performance degradation of the learning process compared to the previous generation (Mitchell, 1998).

Crossover operator

The crossover operator is similar in both real and binary coding, a crossover is a process of exchanges information by exchanging the genes between a two selected chromosomes (Mitchell, 1998; Din, 2008). In this paper a single point crossover was used for each chromosome of the chromosome-pair, where an integer position (k) is selected randomly along the chromosome length. The genes between position (k+1) and L (chromosome length) are swapped to create a new pair of chromosome.

Mutation operator

This operation causes random changes in the components of the chromosomes in the new population. Mutation operation in real-coded GA is different from binary coded. In binary-coding, this operator randomly flips some of the bits in chromosomes from 0's to 1's or

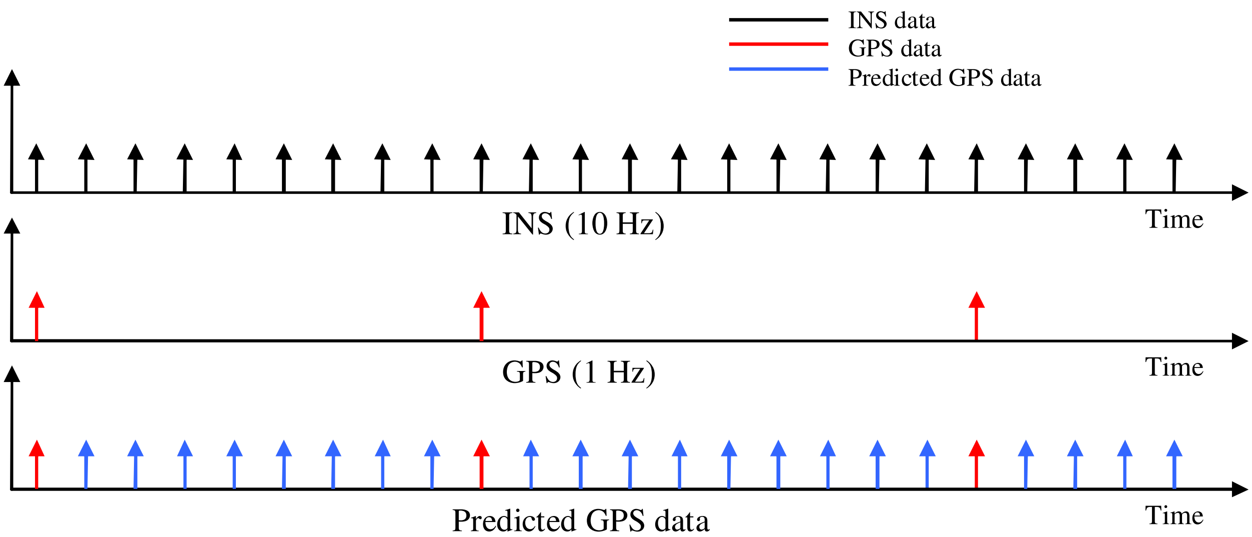


Figure 3. Graphical description of GPS and INS data rate.

vice versa while in real-coded, this operator is implemented by simply replacing the randomly mutated 'gene' with another random number chosen in the same range assigned for the 'gene' in the initial population (Hasan et al., 2010; Hamedi, 2005, Omar et al., 2009).

SUGGESTED INTEGRATION SCHEME

Figure 1 shows the block diagram of the suggested integrated GPS/INS system using the proposed predictor, which consists of INS, and GPS systems, predictor, Integration algorithm, and two subtractions. The INS system is terrestrial strapdown inertial navigation, which measures vehicle latitude, longitude, height, and north, east, down velocities. It is assumed that these measurements are provided every 0.1 second, while the GPS information is available every one second. The predictor is used to predict the GPS information each 0.1 second (GPS information is predicted in nine time instants between two successive GPS measurements), so that the inputs for the integration algorithm is supplied by the difference between INS measurement and GPS information each 0.1 s.

GPS DATA PREDICTION STRATEGIES

Synchronization must be achieved in order to integrate the low rate GPS with the high rate INS system as shown in Figure 3. The synchronization will make it possible to compare the data from both systems in order to realize the proposed integration.

In this paper predicting the missing data of the GPS to be compatible with those of the INS data can solve the difference in sampling rate problem between the two systems. Three strategies are proposed to predict the GPS data (data at intermediate times):

(i) First strategy: The first strategy supposes that the GPS and INS provide reading data each 1 and 0.1 s respectively. It assume that we have the first two reading data at time 1 and 2 s of the GPS and the intelligent predictor will be used to predict the GPS data at time (2.1, 2.2,…., 2.9 s) then the reading data at time 3 s will be already available from GPS system and we do not need to process it to be predicted further more it can be assigned from INS data in order to reduce the deviation of the prediction process. So, the reading data at time 2, and 3 s was available and the ANFIS will predict the GPS data at time (3.1, 3.2,…., 3.9 s) and continue this processing until reach the end of the number of samples. It must be noticed that we predict the reading from time (2.1 to 2.9 s) depending on reading data at time (1 and 2 s) which are already available.

(ii) Second strategy: Since the INS reading data is delivered every (0.1 s) then after 10 reading of INS data was received the estimation process was accomplished to estimate the reading data at time (2.1 s) depending on two previous reading data at times (1.9 and 2 s) and after the processes to estimate the reading data at time (2.1 s) was completed, then we use the data at time 2, and 2.1 s to estimate the data at time (2.2 s) and so on, notice that the data at time (2 s) will be used with the data obtained from the estimation process at time (2.1 s). Figure 4 shows the schematic diagram for predicting GPS data.

(iii)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

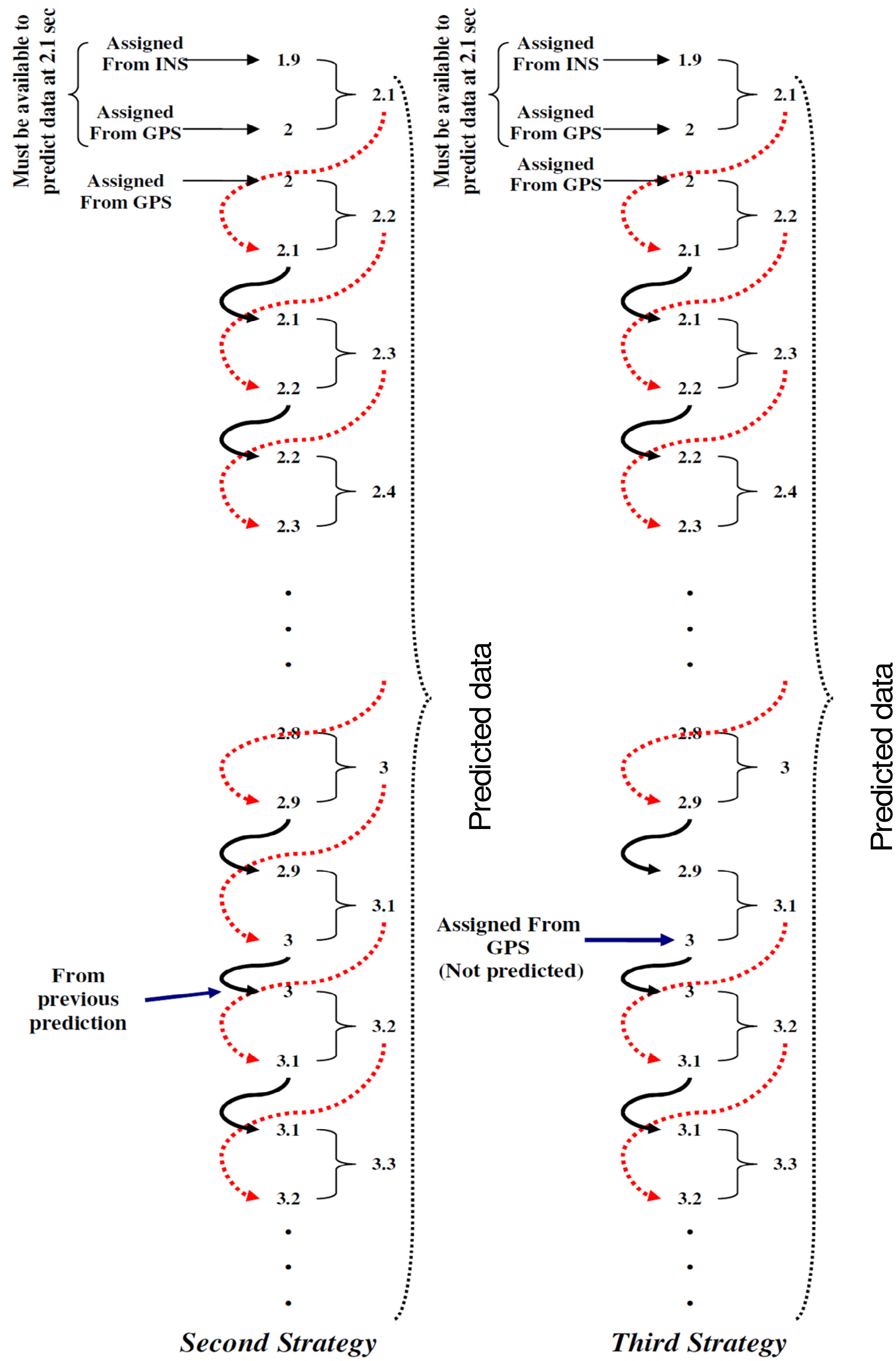


Figure 4. Schematic diagram for predicting missing GPS data.

prediction process to reduce the oscillation, which result from the estimation process. So, the reading data in integer times such as (2, 3, 4 s, …, etc), will be assigned instead of predict them which produce more accurate estimated trajectory.

RESULTS AND DISCUSSION

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. The

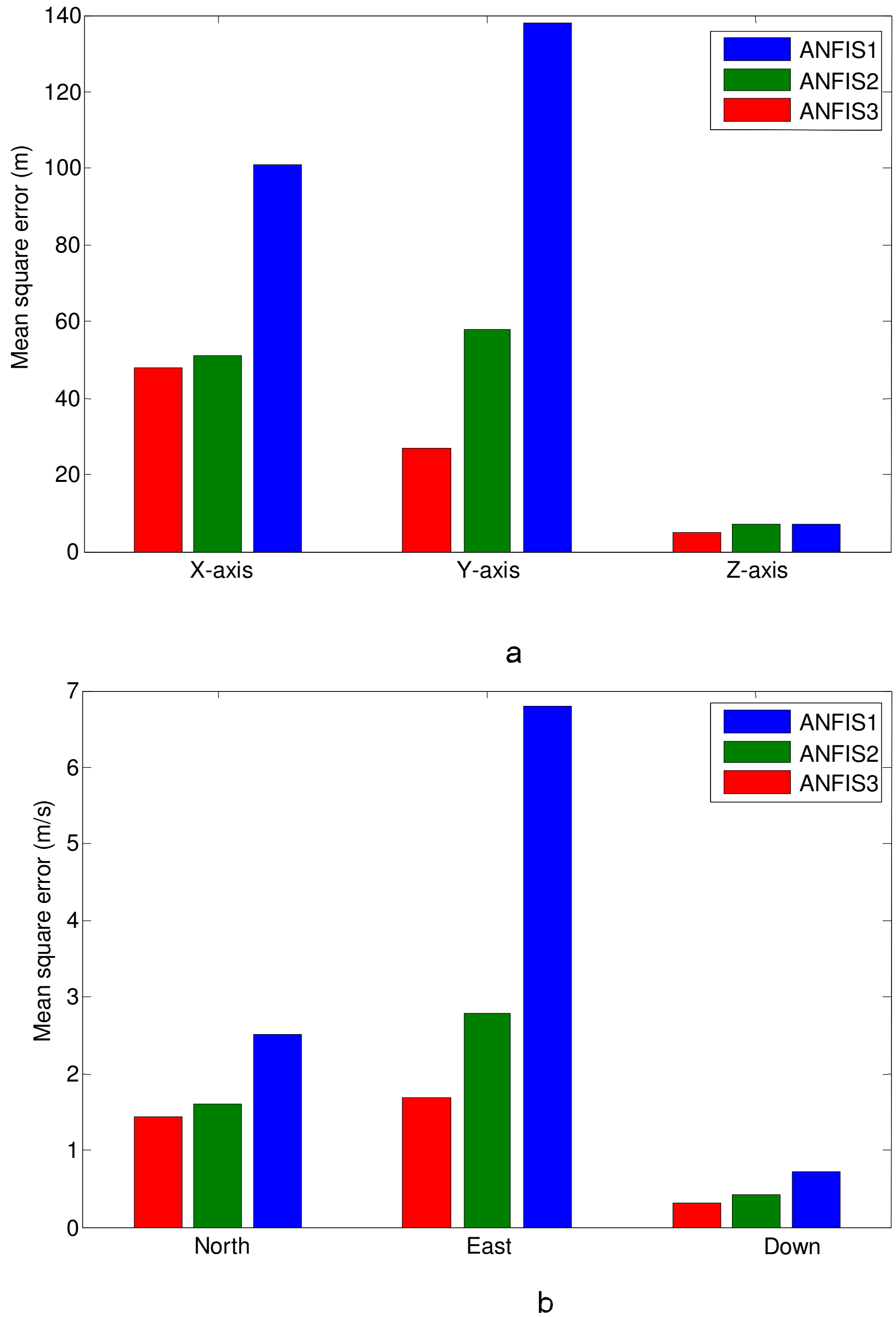
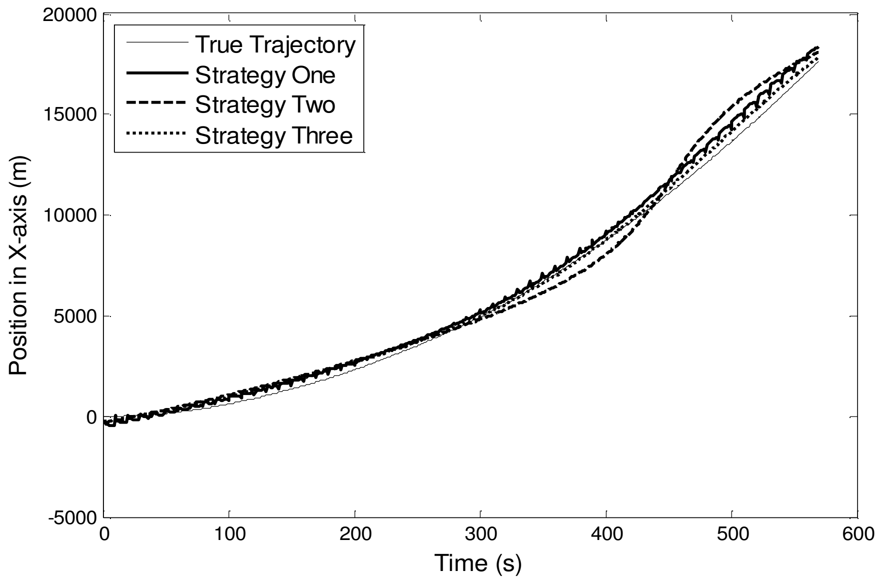
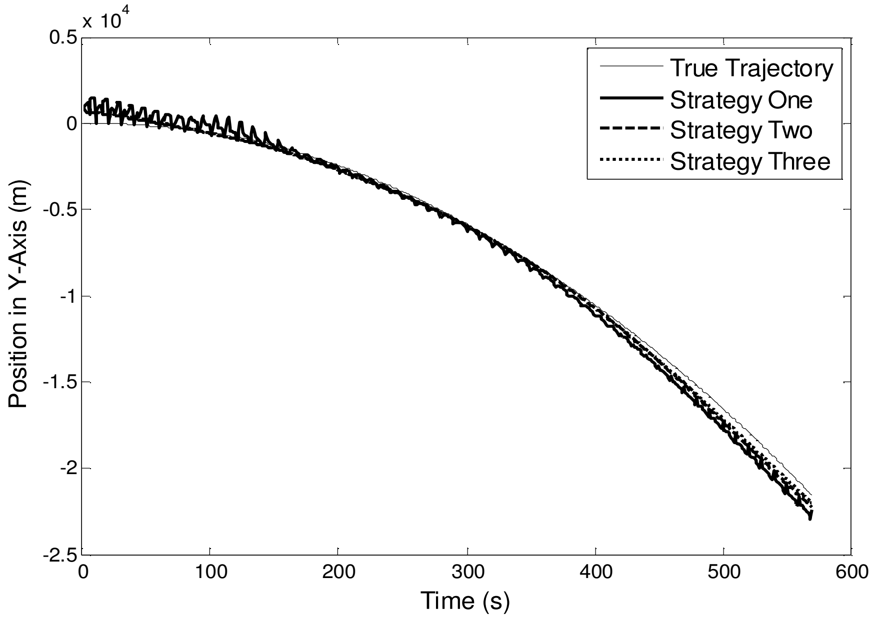


Figure 5. Performance of the intelligent predictor based ANFIS for (a) position, and (b) velocity.

performance of using different assumptions for the proposed strategies on the predicted data and is shown in Figure 5 and the time required for prediction is 0.0047 s. In general, third strategy produces better results, in terms of the mean square error, than the other two strategies since it uses the true trajectory data of the nearest samples to the predicted one. The three strategies give better results in predicting 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 (that is, 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 provides acceptable positions and velocity accuracies compared to the other strategies it is also shown that optimization technique that is used enhances


True Trajectory
Strategy One
Strategy Two
Strategy Three
Position in X-axis (m)
Time (s)
20000
15000
10000
5000
0
-5000
0
100
200
300
400
500
600


x 10^4
True Trajectory
Strategy One
Strategy Two
Strategy Three
Position in Y-Axis (m)
Time (s)
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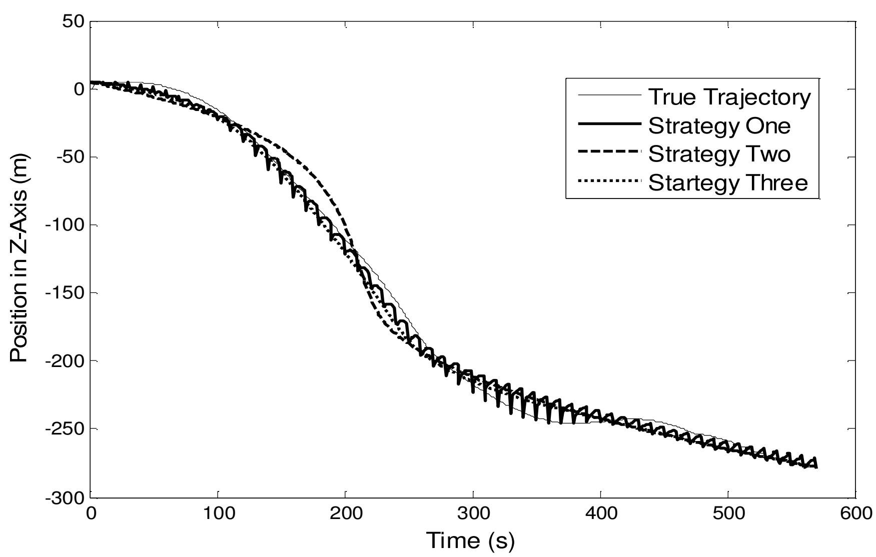
0
-0.5
-1
-1.5
-2
-2.5
0
100
200
300
400
500
600


True Trajectory
Strategy One
Strategy Two
Startegy Three
Position in Z-Axis (m)
Time (s)
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0
-50
-100
-150
-200
-250
-300
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100
200
300
400
500
600

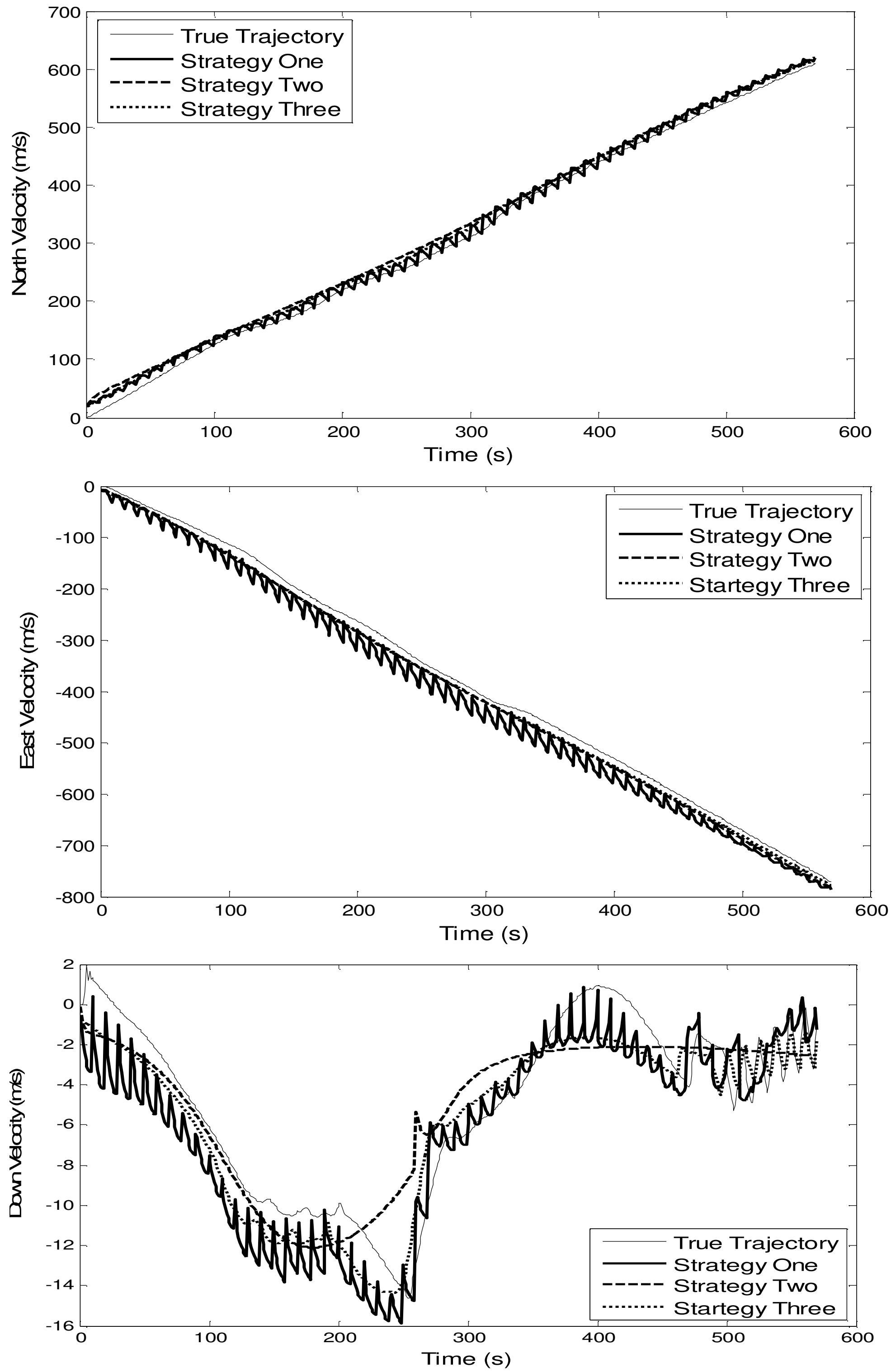

Figure 6. Comparison between the true and predicted trajectories using three strategies for Position and Velocity in all directions.

the accuracy for the prediction process. As shown in Figure 6 by comparing the three proposed strategies with the true trajectory.

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