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GPS/INS integration utilizing dynamic neural networks for vehicular navigation

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ABSTRACT

Recently, methods based on Artificial Intelligence (AI) have been suggested to provide reliable positioning information for different land vehicle navigation applications integrating the Global Positioning System (GPS) with the Inertial Navigation System (INS). All existing AI-based methods are based on relating the INS error to the corresponding INS output at certain time instants and do not consider the dependence of the error on the past values of INS. This study, therefore, suggests the use of Input-Delayed Neural Networks (IDNN) to model both the INS position and velocity errors based on current and some past samples of INS position and velocity, respectively. This results in a more reliable positioning solution during long GPS outages. The proposed method is evaluated using road test data of different trajectories while both navigational and tactical grade INS are mounted inside land vehicles and integrated with GPS receivers. The performance of the IDNN – based model is also compared to both conventional (based mainly on Kalman filtering) and recently published AI – based techniques. The results showed significant improvement in positioning accuracy especially for cases of tactical grade INS and long GPS outages.

1. Introduction

Most of today's land vehicles are equipped with Global Positioning Systems (GPS) to provide accurate position and velocity information. However, there are several situations where GPS experience either total system outage (due to satellite signal blockage) or deterioration of accuracy (due to multipath effects and clock bias error). Therefore, GPS is usually combined with Inertial Navigation System (INS), which is a self-contained system incorporating three orthogonal accelerometers and three orthogonal gyroscopes. These monitor the vehicle's linear accelerations and rotation rates. A set of mathematical transformations and integrations with respect to time are applied to these raw measurements to determine position, velocity and attitude information. However, the INS accuracy deteriorates with time due to possible inherent sensor errors (white noise, correlated random noise, bias instability, and angle random walk) that exhibit considerable long-term growth [1–5].

The integration of GPS and INS, therefore, provides a navigation system that has superior performance in comparison with either a GPS or an INS stand-alone system. For instance, GPS position components have approximately white noise characteristics with bounded errors and can therefore be used to update INS and improve its long-term accuracy. On the other hand, INS provides positioning information during GPS outages thus assisting GPS signal reacquisition after an outage and reducing the search domain required for detecting and correcting GPS cycle slips. INS is also capable of providing positioning and attitude information at higher data rates than GPS.

Kalman filtering (KF) was applied for a number of years to provide an optimal GPS/INS integrated module [3–9]. More recently, several techniques based on Artificial Intelligence (AI) have been proposed to replace KF in order to eliminate some of its inadequacies [10–14]. The major inadequacy related to the utilization of KF for GPS/INS integration is the necessity to have a predefined accurate stochastic model for each of the sensor errors. Furthermore, prior information about the covariance values of both INS and GPS data as well as the statistical properties (i.e. the variance and the correlation time) of each sensor system has to be known accurately.

Several AI – based GPS/INS architectures using Multi-Layer Perceptron Neural Networks (MLPNN) [15], Radial Basis Function Neural Networks (RBFNN) [16] and Adaptive Neuron-Fuzzy Inference Systems (ANFIS) [17] were reported for GPS/INS integration [10–14,18–20]. The main idea behind all of these methods is to mimic the latest vehicle dynamics by training the AI module during

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the availability of the GPS signals. An empirical model that processes the INS output (position or velocity) and provides the corresponding INS position or velocity error can be established during the update (training) procedure. In case of GPS outages, this model operates in the prediction mode to correct for inaccuracies in INS outputs. All of the existing AI – based models relate the INS error at a certain time instant to the INS position or velocity at the same instant. The major drawback of such models is their inability to mimic the INS error trend at either the INS position or velocity during the update procedure. Therefore, in case of relatively long GPS outages, any of the existing AI–based models may not be capable of providing a reliable and accurate positioning solution, especially for tactical and low cost systems. In addition, some of the recently published results showed that KF might outperform some of the AI–based techniques during the first few seconds of the GPS outages [20]. This is due to the inaccurate linearized dynamic model of INS errors utilized by KF. Such linearized model operates adequately only in the short-term of GPS outages. In case of long GPS outages, the ignored non-linear and nonstationary parts of the errors grow to large values and deteriorate the overall positioning accuracy. The negative impact of the inappropriate stochastic models of inertial sensors also appears in cases of long GPS outages [10–14,18–20].

In this research, we aim at developing an AI–based GPS/INS integration module taking into consideration the INS error trend and thus providing a better positioning accuracy during both short and long GPS outages. Such technique combines the advantages of some of the existing models with the advantages of dynamic neural networks in representing the sequential process in the input data (INS position or velocity). In this way, it should be possible for the proposed module to model both the INS position and velocity errors based on the current and some past samples of the INS position and velocity, respectively.

2. Dynamic neural network

2.1. Motivation

The INS dynamic error model used by KF is a linearized one. In addition the stochastic error model for the sensor errors is also linearized in the form of 1st order difference equations. Such state space model is required for the operation of KF. The non-linear and the non stationary parts of the INS errors are not modeled for KF, thus deteriorating the positioning accuracy, especially in the long term. This leads to large position errors in case of relatively long GPS outages. The non-linear complex AI – based modeling capabilities is therefore suggested in this study.

In fact, there are several considerable drawbacks to the use of KF in vehicular navigation application. These include: (1) the necessity of accurate stochastic modeling, which may not be possible in the case of 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 un-stable 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 benefit of utilizing AI-methods over the conventional method (KF) that none of the above KF drawbacks could be found while utilizing the AI-methods. Furthermore, the advantage of utilizing the proposed IDNN over the other AI-methods that IDNN method is performing a temporal processing that gives the model complete information about the temporal relationship of the input pattern, which is the main challenge in studying the INS error that incorporate major temporal dimension.

Dynamic networks are generally more powerful than static networks (although they may be somewhat more difficult to train) [15]. Because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns. In fact, in order to predict temporal patterns, an ANN requires two distinct components: a memory and an associator. The memory holds the relevant past information, and the associator uses the memory to predict future events. In this case the associator is simply a static MLPNN network, and the memory is generated by a time delay unit (or shift register) that constitutes the tapped delay line [15,16]. In fact, the MLPNN model does not perform temporal processing since the vector space input encoding gives the model no information about the temporal relationship of the inputs. Traditional MLPNN is a static and memoryless network that is effective for complex non-linear static mapping. In fact, INS velocity or position error prediction is a procedure where previous states of the INS velocity and position errors have to be seriously considered. Apparently, INS error modeling involves a major temporal dimension and in the ANNs context there are efficient methods to represent and process such models [17].

A common method is to consider a sliding (or moving) window of input sequences. This approach has been widely used with the standard MLPNN [18]. In this case, a fixed number of past items of information are selected and introduced to the input layer of the network. Therefore, the network is provided with a static memory that is specifically expert knowledge-dependent. A major limitation of the MLPNN with a sliding window input sequence is the increase of computational complexity since the input layer has to have a number of neurons equal to the number of past samples. For instance, if it is required to model the error based on the input at the present time instant and the past two samples, the MLPNN input layer should have three input neurons. As a result, both the network complexity and training time will dramatically increase [15].

2.2. IDNN – Input-Delay Neural Network

Another way of dealing with temporal patterns is the use of an internal time delay operator within the MLPNN network. This leads to the time delay neural network, also referred to as the Input-Delay Neural Network (IDNN). In this case, the static MLPNN is transformed into a dynamic network by replacing each static synaptic weight with a finite-impulse response filter. Thus, the number of the embedded time delays provides the network with a short-term memory. The number of neurons associated with the input layer is equal to the number of input variables; therefore, the IDNN integrates temporal context information implicitly and it thus recognizes temporal patterns that have arbitrary time intervals or arbitrary lengths of temporal effects. Thus the IDNN is suitable for situations where temporal patterns should be considered. This has a beneficial effect on the prediction accuracy, which is the major objective of this study. Furthermore, the IDNN can be trained even with the standard back-propagation algorithm [16].

Fig. 1 shows the general architecture of an Input-Delay Neural Network in addition to zooming on the internal structure of a single neuron. The case shown in Fig. 1 considers a tapped delay line that involves the P most recent inputs. In this example, we show three delay elements represented by the operator D. For a case of p delay elements and an input variable $x(t)$, the network processes $x(t)$, $x(t-1)$, $x(t-2)$, ... and $x(t-p)$, where p is known as the tapped delay line memory length [16]. Therefore, the input signal $S_i(t)$ to the neuron i (Fig. 1) is given as:

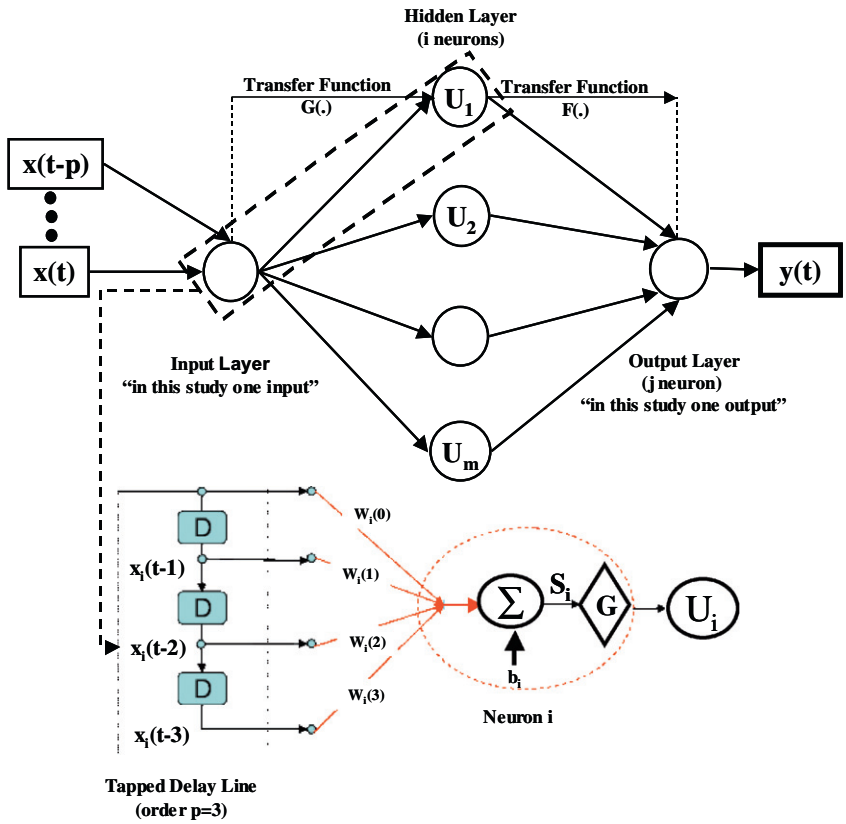


Fig. 1. Input-Delayed Neural Network architecture and single neuron calculations.

$$S_i(t) = \sum_{k=0}^{p} w_i(k)x(t-k) + b_i \tag{1}$$

where $w_i(k)$ is the synaptic weight for neuron i, and b_i is its bias. Then the output of this neuron (U_i) is obtained by processing $S_i(t)$ by the non-linear activation function $G(.)$, chosen as a sigmoid activation function of neuron i.

$$U_i = G\left(\sum_{k=0}^{p} w_i(k)x(t-k) + b_i\right) \tag{2}$$

$$G(S_i(t)) = \frac{1}{1+e^{-S_i(t)}} \tag{3}$$

The output of the IDNN, assuming that it has one output neuron j, a single hidden layer with m hidden neurons, and one input variable as shown in Fig. 1, is given by

$$y_j(t) = F\left(\sum_{i=1}^{m} w_{ji}U_i + \alpha_j\right) \tag{4}$$

where $F(\cdot)$ is the transfer activation function of the output neuron j (which can be chosen to be a sigmoid or a linear function), α_j is its bias and w_{ji} is the weight between the neurons of the hidden layer and the neuron of the output layer.

During the update procedure, we use a second-order back-propagation variation; namely the Levenberg–Marquardt back-propagation (LMBP). The network training process is performed by providing input–output data to the network, which targets minimizing the error function by optimizing the network weights. LMBP uses the second derivative of the error matrix (E) to update the weights of the network in a recursive fashion [15,16].

3. Methodology

The proposed IDNN-based GPS/INS integration module establishes models for both INS position and velocity errors along the East, North and vertical directions, to reliably describe INS error trends and to compensate for their impact during GPS outages. The robustness of these error models will be guaranteed through the application of early stopping criterion during the update (training) procedure of the IDNN-based module while the GPS signals are available. Moreover, the real-time realization will be based on the use of a non-overlap moving window, where the GPS/INS data window moves in real-time with steps equal to the window size. This windowing scheme has several advantages over the conventionally one time-step sliding window method [19].

3.1. Model configuration

Along each of the East, North and vertical directions, the INS velocity (V_{INS}) and the time (t) are the inputs to one of the IDNN modules while the error in the corresponding INS velocity (δV_{INS}) is the module output. During the availability of the GPS signal, the IDNN module operates in the update mode. In order to train the network, the INS velocity error provided at the output of this IDNN module should be compared to a certain target or a desired response. In this case, the target (or true) INS velocity error $\delta V_{INS|GPS}$ is the difference between the INS original velocity and the corresponding GPS velocity:

$$\delta V_{INS|GPS} = V_{INS} - V_{GPS} \tag{5}$$

The difference between IDNN module output (δV_{INS}) and the true velocity error $\delta V_{INS|GPS}$ is the estimation error ($\Delta(\delta V)$) of the IDNN module. In order to minimize this error, the IDNN module

is trained to adjust the IDNN parameters that are continuously updated according to the least square criterion until reaching certain the minimal mean square estimation error (MSE). The training procedure continues and is repeated for all GPS/INS data windows until a GPS outage is detected.

When the satellite signal is blocked (during GPS outages), the system is switched to the prediction mode where the IDNN module is used to process the INS velocity V_{INS} at the input and predict the corresponding velocity error (δV_{INS}) using the latest IDNN parameters obtained before losing the satellite signals. The error is then removed from the corresponding INS velocity component to obtain the corrected INS velocity (V_{INSC}).

$$V_{INSC} = V_{INS} - \delta V_{INS} \tag{6}$$

In order to utilize the IDNN-based $V - \delta V$ module in real-time GPS/INS integration, a non-overlap moving window with certain window size (W) is considered. A number of samples (equal to W) of INS velocity component V_{INS} and the corresponding GPS velocity V_{GPS} are collected. The update procedure of the $V - \delta V$ IDNN parameters starts after collecting the Wth sample of both INS and GPS velocity components. The patterns of INS and GPS velocity components obtained over the data window are used to train the IDNN module to mimic the latest vehicle dynamics and the INS error trend. It is also used to determine the optimal value of the IDNN parameters and to provide an estimate of the (δV_{INS}). The IDNN module is trained until a certain minimum of MSE is reached or after completing a certain number of training epochs. This procedure is repeated after collecting completely new patterns of INS and GPS of a size equal to the window size without considering any of the data samples utilized in the previous window. We decided to utilize non-overlap windowing instead of the conventional sliding window to implement the real-time procedure of IDNN-based GPS/INS in this study. This is due to the fact that non-overlap windowing is less computationally expensive [19,20].

To provide a complete navigation solution for a moving vehicle, each of the three directions involves two IDNN modules ($V - \delta V$ and $P - \delta P$); i.e. the first for the INS velocity error and the second for the residual INS position error. The velocity errors are presented in (km/h) while the position errors of the latitude and longitude IDNN modules are provided in meters (instead of radians or degrees) to represent the errors in determining the vehicle position along the North and East directions, respectively. In fact, in this study and because of being concerned with land vehicle navigation, we will only focus on the horizontal position and velocity components along both the North and East directions.

3.2. INS errors and the input delay process

If INS position and velocity errors are examined, one can determine that they are accumulative, usually grow over time and follow a certain trend. It may not be possible to accurately mimic and appropriately model this trend with an AI-based model that relates the INS error to the corresponding INS output (either position or velocity) for a certain time instant. Therefore, a collection of a particular number of past INS position or velocity sequence has to be presented to the model in order to capture the trend of the error pattern, thus establishing an accurate model of the INS errors. This can be realized by employing the Tapped Delayed Line (TDL) approach by which the last m values $x(t), x(t-1), \ldots, x(t-m)$ of a signal $x(t)$ (corresponding to either INS position or velocity) are simultaneously presented at the input layer of the network.

In this study, one and two time-step input delay sequences will be considered. The second-order delay effect will be considered by training the IDNN model to experience, in the input layer, the previous one time-step sample in addition to the present INS position or velocity sample. Moreover, the higher-order error can be considered by having two and three time-step delay inputs. In Section 5.1, the impact of using one and two input delay elements will be demonstrated and discussed.

3.3. Network over-fitting

Network over-fitting is a classical machine-learning problem that has been investigated by many researchers [16,17]. Network over-fitting usually occurs when the network captures the internal local patterns of the training data set rather than recognizing the global patterns of the data sets. The knowledge rule-base that is extracted from the training data set is therefore not general. As a consequence, it is important to realize that the specification of the training samples is a critical factor in producing a neural network which is capable of making the correct responses. Two procedures have been evaluated to overcome the problem of over-fitting namely, early stopping and regularization.

3.3.1. Early stopping

In general, the aim of early stopping is to mimic the prediction of future individuals from the population [21]. This will be achieved in case that the training data fully represents the sample space and each left out individual can lie anywhere in this space. Large samples and small dimensionality generally satisfy these requirements.

During the update stage (training), the module performs the function of understanding the input/output mapping as shown in Fig. 2. To ensure the generalization of the IDNN module a hold out kind of early stopping procedure is used [21]. The hold out early stopping criterion was chosen due to its suitability for real-time implementation, as the computational time is a substantial limitation.

As depicted in Fig. 2 the part of INS data used by the early stopping criterion corresponds to the intermediate interval between the update (training) and prediction stages. This approach allows IDNN to readjust its parameters to detect the dynamics of the data in a transition interval before moving to the prediction stage. Furthermore, it avoids the possibility of model over-fitting for the training data. It should be noted that the procedure shown in Fig. 2 is applied for all velocity and position components (six components). In the presence of a GPS signal, the early stopping criterion is applied while updating each network. In principle, the generalized IDNN parameters are those associated with the minimum data set model error during the early stopping procedure of the update stage. The generalized IDNN during the update stage is used in case of GPS outages to predict the INS position or velocity error. This is instantaneously subtracted from the corresponding INS position or velocity to get the corrected INS position or velocity.

3.3.2. Regularization

The second method utilized to avoid the over-fitting problem and to optimize the IDNN model is the regularization technique [15]. This is known to be a very desirable procedure when the scaled conjugate gradient descent method is adopted for training, which is the case in this study. The regularization technique involves modifying the performance function (MSE), which is normally chosen to be the sum of squares of the error between the network output (Y_P) and the desired response (Y_o) on the training data set defined as:

$$\mathrm{MSE} = \frac{1}{2}\sum_{i=1}^{n}(Y_{O_i} - Y_{P_i})^2 \tag{7}$$

The modified performance function MSE_{reg} is defined in Eq. (8) as the sum of the weighted mean of the sum of squares of the network weights and the weighted original MSE function as

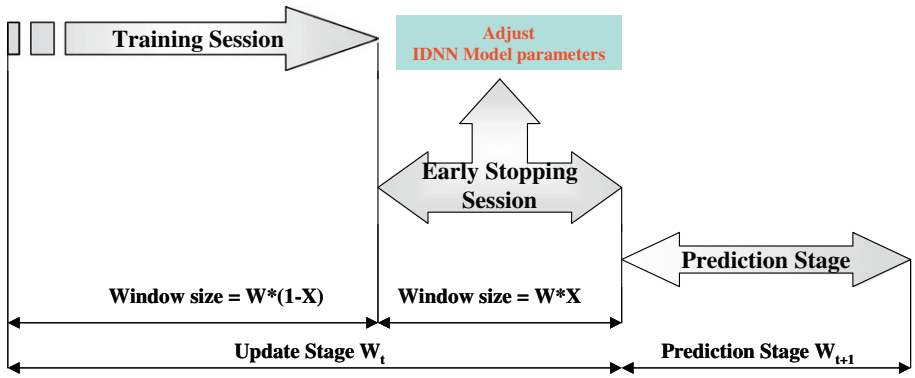


Fig. 2. Time line index for the model' stages sequences.

$$\mathrm{MSE}_{\mathrm{reg}} = \gamma \times \mathrm{MSE} + (1-\gamma) \times \mathrm{MSW} \tag{8}$$

where γ is the performance ratio that takes values between 0 and 1, $\mathrm{MSE}_{\mathrm{reg}}$ is the regularized performance function and MSW is computed as:

$$\mathrm{MSW} = \frac{1}{M}\sum_{j=1}^{M} w_j^2 \tag{9}$$

where M is the number of weights utilized inside the network structure. Using the performance function of Eq. (9), all the IDNN modules were developed with the intention to avoid over-fitting of the data in order to provide reliable model for INS position and velocity errors along the three directions.

4. Road test experiments

The performance of the proposed IDNN-based GPS/INS integration module was examined with two field tests (Tests I and II) involving two different navigation systems. Test I utilizes CIMU navigation grade INS and a NovATel OEM-4 GPS receiver. Over the whole trajectory of Test I (shown in Fig. 3), no natural GPS outages were detected, and thus the position and velocity information obtained from this system in the differential mode will be used as a reference when evaluating the accuracy of the system. On the other hand, Test II utilizes a tactical grade INS system (IMU-Honeywell HG1700) and a NovAtel OEM4 GPS receiver. The trajectory (shown in Fig. 4) was totally different from that of Test I. A minimum of seven GPS satellites was available throughout Test II and

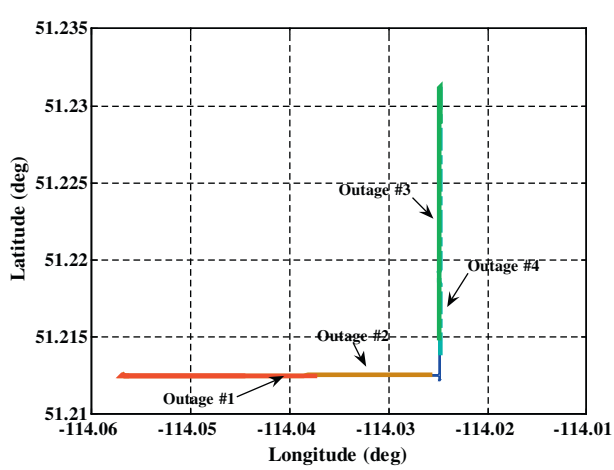


Fig. 3. Test trajectories I showing the locations of GPS outages.

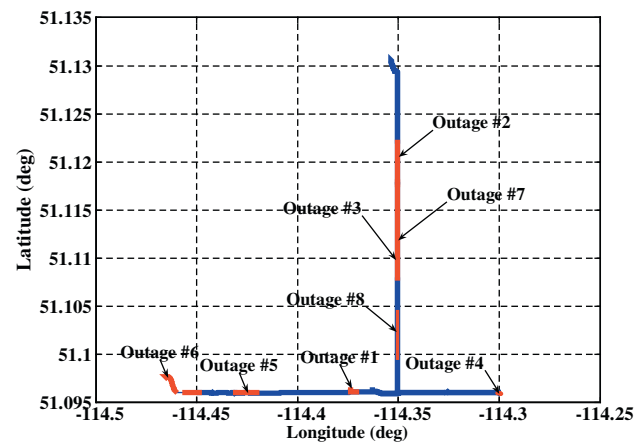


Fig. 4. Test trajectories II showing the locations of GPS outages.

differential GPS information can be obtained and used as was reported in [20,22].

The performance of the IDNN module is examined during artificial 100 s GPS outages intentionally introduced to both trajectories in order to test its ability to accurately predict the INS errors and provide reliable position and velocity information. Ten and four artificial GPS outages were selected at different locations along Tests I and II, respectively. Since the GPS position was available during the entire experiment, the performance of the proposed IDNN module is evaluated by comparing its output to that of the GPS, which was considered as a reference. These artificial GPS outages were selected at locations of different vehicle dynamics so that the system stability and robustness can be examined.

The IDNN modules were initialized and continued to update while the GPS signal is available. The real-time implementation considered 40 s window size during the update procedure, which is performed to minimize the error between the IDNN output and the desired response such that RMSE of 10^{-4} is achieved. However, given the real-time implementation constraint of processing time, the IDNN update procedure for each window was terminated after 100 training epochs apart from the RMSE achieved.

In order to examine the value of the proposed IDNN-based module for GPS/INS integration, it is essential to compare the positioning accuracy of the IDNN model to the conventional techniques, predominantly based on KF, and the recently published AI-based module [20,22].

For both road tests, the model results are compared to KF results, which are considered as the base line accuracy level for vehicle positioning. The KF results were obtained using AINS™, a

program developed and provided by the Mobile Multi-Sensor Systems Research Group at the University of Calgary, Calgary, Canada [22]. This program processes the INS and GPS data using a 15 state KF, where the states include three position errors, three velocity errors, three attitude errors, three gyroscope bias errors and three accelerometer bias errors.

In addition, the model results for Test I are compared with the recently AI-based model utilizing Radial Basis Function Neural Network (RBFNN) for the same trajectory and identical GPS outages. This model is developed by the Navigation and Instrumentation Research Group, Royal Military College (RMC), entitled the AI-base Segmented Forward Predictor (ASFP). Basically, the model provides forward prediction of INS velocity and position errors to enhance the overall positioning accuracy [20].

5. Results and discussion

The proposed IDNN – based GPS/INS module is examined and analyzed during both the update (training) and prediction modes of operations using the navigational grade INS data of Test I. The benefits of early stopping and the impact of the number of input delay elements are also explored. Performance validation on another trajectory while using other types of navigation systems is performed using the tactical grade INS data of Test II.

5.1. Test I – navigational grade GPS/INS

This trajectory was run for approximately 1200 s and thus only four GPS outages were considered. Both 40 and 100 s GPS outages were examined in order to evaluate the effectiveness of the proposed IDNN module under different dynamics for both short and long outages. The locations of the GPS outages were chosen so that different vehicle dynamics were experienced during each outage. Here, it should be noticed here that the model is trained with a data equal to a window size (40 s) just before the starting of the outages. Thus, the model is evaluated by training with a particular pattern of INS error trend during update stage. This pattern is different from the one experienced during the GPS outage.

The parameters associated with the IDNN modules change through the update procedure to achieve a predefined error target between the actual INS error ($\delta P_{INS|GPS}$ or $\delta V_{INS|GPS}$) and the IDNN output (δP_{INS} or δV_{INS}). In parallel, the early stopping criterion is applied utilizing input vectors from the INS and GPS position or velocity components on which the IDNN module was not trained. This input data (P_{INS} or V_{INS}) is presented to the trained IDNN module to examine its capability to accurately predict the corresponding output data (δP_{INS} or δV_{INS}). As shown earlier in Fig. 2, a fraction X of a data window of size W (i.e. $X * W$) has to be chosen for the early stopping procedure. It is important to choose this part of the input data so that it is big enough to be representative of the

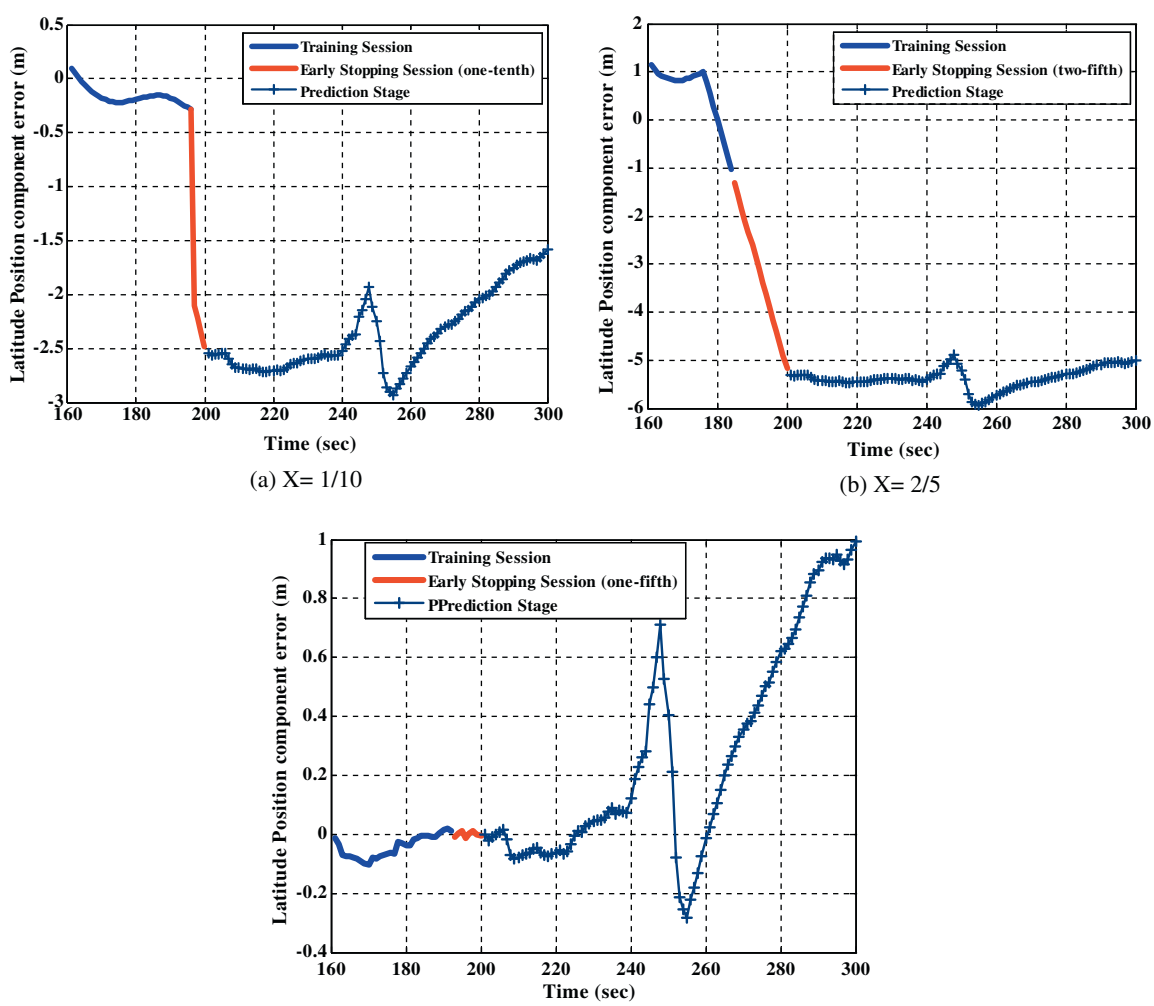


Fig. 5. The model performance during training, early stopping and prediction utilizing different value of X.

existing features (monitored vehicle dynamics). We have, therefore, decided to examine the performance of the update procedure while choosing the size of the data record used by the early stopping criterion to be equal to one-tenth, one-fifth and two-fifth of the window size as shown in Fig. 5. This figure shows the output of the IDNN module for the latitude position component during the training, early stopping and prediction procedures just before and during the GPS Outage #1. Apparently, if two-fifth (16 s) of data was used by the early stopping criterion, the IDNN was not well trained and as a result an error of about 1 m was observed at the end of training (see Fig. 5b). Consequently an error of about 6 m was observed during the GPS outage. The main reason for this is that there was not enough data record for the training process (only three-fifth or 24 s), which made it difficult to reach the error goal. On the other hand, when one-tenth (4 s) of the data was relatively short for the early stopping criterion to function appropriately. As a result an error of about 3 m was observed during the GPS outage (see Fig. 5a). Therefore, it was decided to select the percentage X of the data set for early stopping to be one-fifth (8 s) of the window size. This choice gave the training procedure enough time to reach about 0.1 m error. It also gave enough data record for the early stopping criterion so that less than 1 m position error was detected during the GPS outage (see Fig. 5c). The performance during the three cases shown in Fig. 5 was observed during the training, early stopping and prediction stages of the other three GPS outages and for the other position components.

The regularization technique described in Section 3.3.2 was applied to improve the generalization of the training process of the 6 networks. A trial and error procedure is applied to determine the best value of the ratio γ. Since changing the value of γ has a very minor effect on the overall performance of the system, there was no real need to employ an optimization technique to determine the optimum value of γ. Different values of γ between 0 and 1 are examined for each network and it was determined that a γ ratio equal to 0.8 provided a consistent accuracy level for all networks.

To investigate the effect of time dependence of the INS error (the output of the IDNN module) on the present and past INS inputs (the input to the IDNN module), we examined the performance of the IDNN position modules during the four GPS outages. In this analysis, we compare the performance of the IDNN module using one time input delay element to the case of two input delay elements and the conventional case of the non-input delay elements. As can be depicted from Table 1, the worst positioning accuracy (for both North and East components) for all GPS outages was observed for the case of the non-input delay network architecture. Also, it can be determined that significant enhancements (20–50%) took place in the positioning accuracy when utilizing one or two-time-step input delay architectures. On the other hand, the results clearly show that utilizing two input delay elements has insignificant improvements to the model performance if compared to the one input delay IDNN architecture. While the proposed IDNN-based module showed slight accuracy improvement when using two input delay elements instead of one, the additional delay element significantly complicated the update procedure (thus requiring a long training time), which is not desirable for real-time applications. In fact, we noticed that when the IDNN module employed two input delay elements instead of one, the processing time during training and early stopping stages was almost doubled.

Based on the above analysis, the proposed IDNN module considers a 40 s window size, one delay element at the input layer and one-fifth (8 s) of the data for the early stopping criterion. Fig. 6a and b show the location of each of the 100 s GPS outages along the longitude and the latitude components, respectively. Fig. 6c and d illustrate the associated error distribution. It can be depicted that the IDNN provides a consistent level of accuracy for both position components for all GPS outages except for the longitude during the second GPS outage (8 m error as noticed in Fig. 6c). Apparently, while the vehicle was subject to a noticeable change in the longitude during the whole 2nd GPS outage, the update procedure (just prior to this outage) was for a training pattern corresponding to no longitude changes (see Fig. 6a). However, such level of accuracy (8 m over 100 s GPS outage) is better than the output of the other models such as KF (18 m) and a recently developed AI technique (12 m) on the same trajectory [20]. Such superior performance over other techniques is due to the utilization of input delay elements. More details about the comparison with other models will be presented hereafter.

A comparison to both KF and ASFP was performed for both the longitude and latitude position components during the 40 and 100 s GPS outages. Table 2 shows the average largest position error (ALPE) for each case. Although, the IDNN shows the same level of accuracy in case of short GPS outages (40 s), it provides a significant improvement over both KF and ASFP in case of long GPS outages (100 s) [20]. It can be observed from Table 2, that IDNN results appear to be similar for both position components, in case of 40 s GPS outages if compared with KF results, which was the advantage of utilizing KF over ASFP. In addition, a similar observation could be made in case of long GPS outages so that it can be determined that the IDNN model outperforms the ASFP model, which was the advantage of utilizing ASFP over KF. In other words, the proposed IDNN module combines the benefits from both ASFP and KF models.

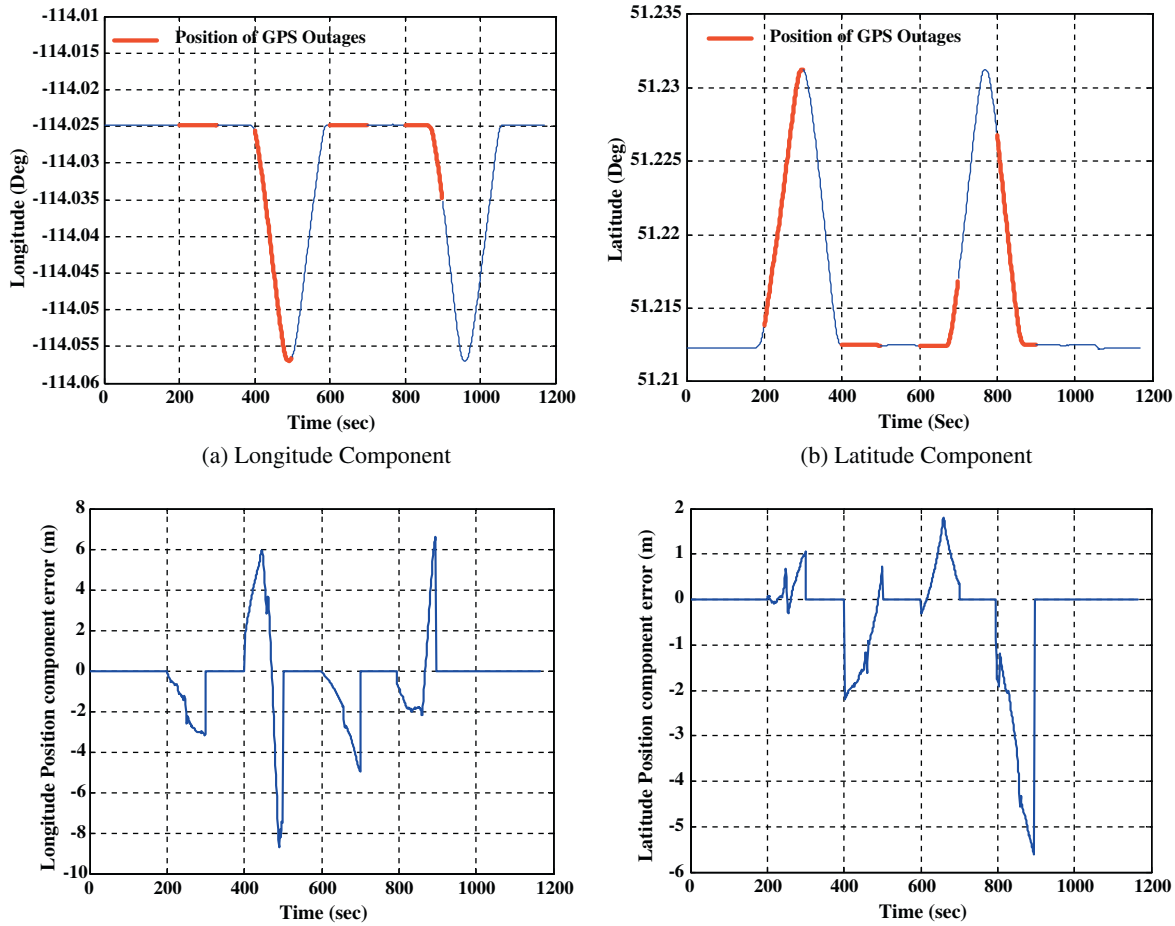
For further analysis, a performance indicator namely the error increase rate (EIR) defined by Eq. (10) is introduced. EIR is calculated as the difference between the average position error from the case of 40 s GPS outage and the corresponding one for the case of 100 s GPS outage divided by the latter.

$$\mathrm{EIR} = \frac{(\mathrm{ALPE}_{100\ \mathrm{s}} - \mathrm{ALPE}_{40\ \mathrm{s}})}{\mathrm{ALPE}_{100\ \mathrm{s}}} \tag{10}$$

This indicator is suggested to analyze and examine the ability of the proposed IDNN module to minimize the increase rate of INS error over long GPS outages. Examining Table 2 carefully, it can be concluded that the IDNN module provides the lowest EIR, which indicates that the IDNN method is able to mimic the pattern of the INS error increase much better than both KF and ASFP methods.

Table 1
The highest position error utilizing different input delay sequences.

Outage #	Maximum position error (m)					
	Non-input delay		One-time delay element		Two-time delay elements	
	North	East	North	East	North	East
#1	1.8	4.9	1.0	3.1	1.0	3.0
#2	2.9	11.1	2.2	8.0	2.1	7.9
#3	3.7	6.8	1.8	4.3	1.5	4.3
#4	7.4	7.8	5.5	6.2	5.4	6.0



(a) Longitude Component (b) Latitude Component

(c) Error for Longitude (4 outages) (d) Error for Latitude (4 outages)

Fig. 6. The position error distribution along GPS outages as results from IDNN model Test I.

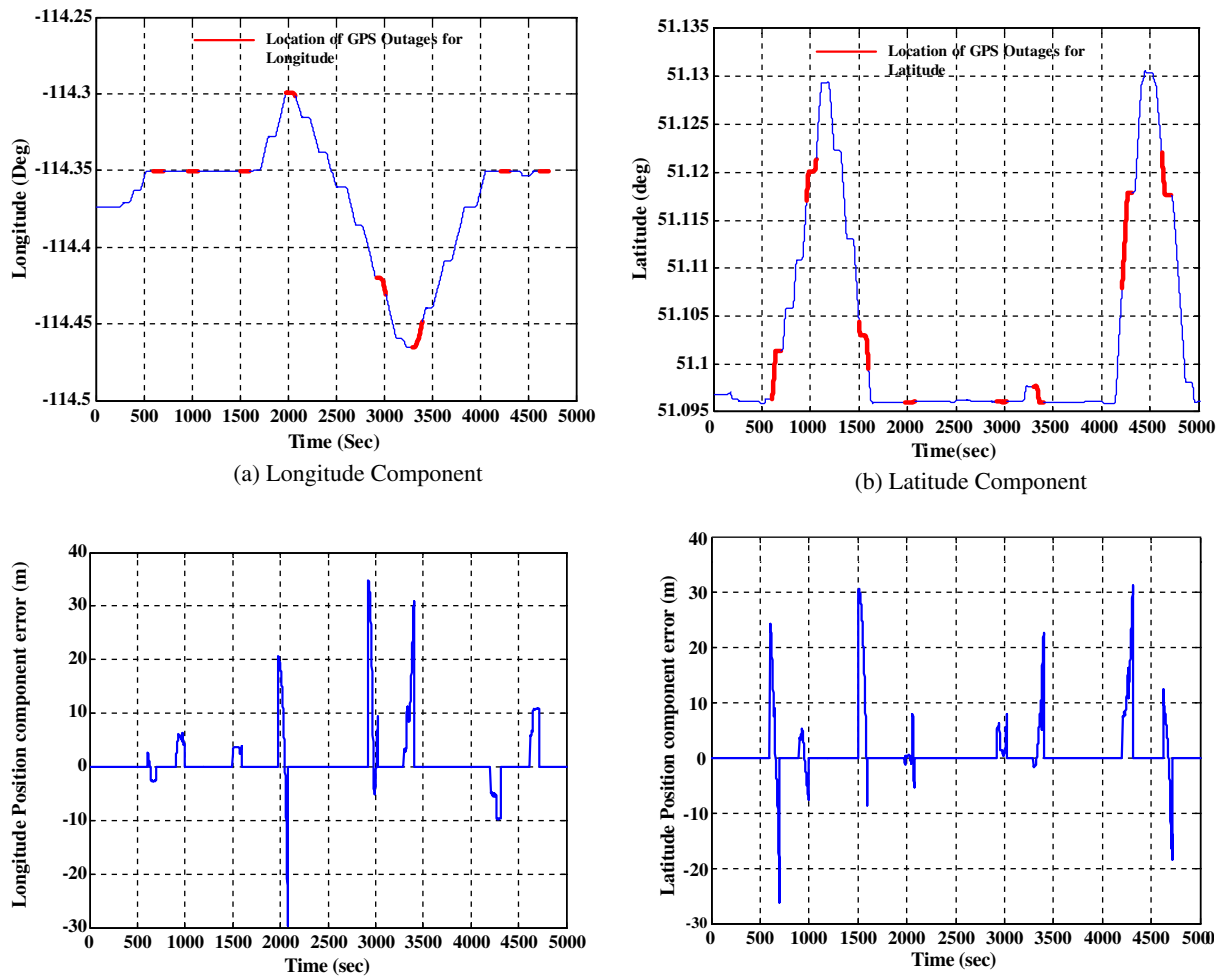
Table 2
Summary of average position errors for 40 and 100 s GPS outages and the EIR% using different models utilizing Test I.

GPS outage	Component	IDNN case ALPE (m)	ASFP case ALPE (m)	KF case ALPE (m)
40 s	Latitude	1.8	2.5	1.9
	Longitude	3.8	3.5	3.6
100 s	Latitude	2.7	4.7	7.1
	Longitude	5.9	6.8	8.6
EIR%		IDNN case	ASFP case	KF case
	Latitude	33	47	73
	Longitude	36	49	58

5.2. Model validation utilizing Test II

In order to validate the proposed IDNN module, it is essential to examine the model with another road test trajectory involving different type of INS. The importance and the benefits of the proposed technique appear more when it is applied to tactical grade INS. This type of INS is much less expensive than navigation grade unit and thus very useful in a variety of applications. However, the relatively larger bias drift and scale factor instabilities of the accelerometers and the gyroscopes of tactical grade INS affect the positioning accuracy. Test II trajectory (Fig. 4), which involves a tactical grade INS is evaluated utilizing the same IDNN model configuration developed for Test I (40 s window size, 8 s data record for early stopping and one input delay element). In order to examine the performance of the system on a tactical grade INS for long GPS outages, eight outages (100 s each) at different locations and corresponding to different vehicle dynamics were considered along the trajectory, as shown in Fig. 7a and b for the longitude and latitude position components, respectively. In fact, most tactical grade GPS/INS data fusion methods showed satisfactory positioning accuracy only for 30 or 40 s GPS outages. In some applications, GPS outages may extend to about 100 s in areas that include urban canyons. Therefore, in this study, it was decided to show the performance for 100 s GPS outages in order to examine the robustness of the IDNN module for these kinds of applications.

Fig. 7c and d, respectively, show the longitude and the latitude position errors for the 8 GPS outages. For a tactical grade INS, this level of accuracy is much more than expected from a data fusion model during 100 s GPS outage. In order to justify this, the performance shown in Fig. 7 using IDNN module was compared to KF and



(a) Longitude Component

(b) Latitude Component

(c) Error for Longitude (8 outages)

(d) Error for Latitude (8 outages)

Fig. 7. The position error distribution along GPS outages as results from IDNN model Test II.

Table 3
Summary of position errors for 100 s GPS outages using different models utilizing Test II.

Position component	Method	1st Outage	2nd Outage	3rd Outage	4th Outage	5th Outage	6th Outage	7th Outage	8th Outage
Longitude	IDNN	2.86	5.92	2.53	30.05	33.50	30.91	9.82	10.13
	ASFP	3.71	*5.49*	14.11	43.33	44.51	34.49	10.63	11.32
	KF	7.09	10.25	21.21	63.26	70.19	41.15	13.85	16.08
Latitude	IDNN	26.25	8.45	30.32	8.20	8.25	22.12	30.93	18.95
	ASFP	*26.09*	17.86	31.82	*7.87*	21.71	31.16	*28.21*	25.32
	KF	29.43	24.14	40.32	11.51	35.16	45.92	40.32	69.27

ASFP one the results are shown in Table 3 for 100 s GPS outages. Obviously, IDNN module outperforms KF for all GPS outages and offers much better accuracy in most of the outages. On the other hand, ASFP provides less position error than IDNN for only four cases (highlighted in Table 3). However, one can notice that, for any of these four cases, there was only slight improvement (less than 2 m position error) over the IDNN module. Moreover, superior performance over the ASFP method can be noticed in Table 3 for most of the 8 GPS outages for both position components.

6. Conclusions

This research introduced a new technique for GPS/INS integration based on IDNN that mimics the INS error trend and provides reliable estimates for INS position and velocity errors. The IDNN module relies on input delay elements at the input layer so that the output INS position or velocity error is modeled based on the present and past samples of the corresponding INS position or velocity. Consequently, the time dependence feature of the INS errors was appropriately modeled. In addition, the common over-fitting problems during the training procedure of the IDNN module were avoided by adopting both the early stopping criterion and the regularization procedure. The impact of different delay elements at the input layer on the overall positioning accuracy was investigated. In comparison to conventional and recent AI – based GPS/INS integration techniques, the IDNN module showed superior performance during both short and long GPS outages.

References

[1] J. Lobo, P. Lucas, J. Dias, A. Traca de Almeida, Inertial navigation system for mobile land vehicles, in: Proceedings of the IEEE International Symposium on Industrial Electronics ISIE '95, vol. 2, July 1995, pp. 843–848.

[2] N. El-Sheimy, K.P. Schwarz, Integrating differential GPS receivers with an inertial navigation system (INS) and CCD cameras for a mobile GIS data collection system, in: Proceedings of the International Society for Photogrammetry and Remote Sensing Conference, Ottawa, Canada, 1994, pp. 241–248.
[3] J. Farrell, The Global Positioning System and Inertial Navigation, McGraw-Hill Professional, 1998.
[4] D.K. Mynbaev, Errors of an inertial navigation unit caused by ring laser gyro errors, in: Proceedings of the IEEE Position Location and Navigation Symposium, 1994, pp. 833–838.
[5] A. Noureldin, D. Irvine-Halliday, M.P. Mintchev, Accuracy limitations of FOG-based continuous measurement-while-drilling surveying instruments for horizontal wells, IEEE Trans. Instrum. Meas. 51 (6) (2002) 1177–1191.
[6] R.V.C. Wong, K.P. Schwarz, M.E. Cannon, High-accuracy kinematic positioning by GPS-INS, Navig.: J. Inst. Navig. 35 (1988) 275–287 (Summer).
[7] G. Dissanayake, S. Sukkarieh, The aiding of a low-cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications, IEEE Trans. Robot. Automat. 17 (5) (2001) 731–747.
[8] R. Hirokawa, K. Nakakuki, K. Sato, R. Ishihara, Threading the maze GPS/INS landmark sensing and obstacle avoidance, GPS World (2004) 20–26.
[9] S. Nassar, A. Noureldin, N. El-Sheimy, Improving positioning accuracy during kinematic DGPS outage periods using SINS/DGPS integration and sins data de-noising, Surv. Rev. 37 (292) (2004) 426–438.
[10] A. Noureldin, A. Osman, N. El-Sheimy, A neuro-wavelet method for multi-sensor system integration for vehicular navigation, J. Meas. Sci. Technol., Lond., UK 15 (2) (2004) 404–412.
[11] N. El-Sheimy, K.-W. Chiang, A. Noureldin, Developing a low cost MEMS IMU/GPS integration scheme using constructive neural networks, IEEE Trans. Aerosp. Electron. Syst. 44 (2) (2008) 582–594.
[12] R. Sharaf, A. Noureldin, A. Osman, N. El-Sheimy, Online INS/GPS integration with a radial basis function neural network, IEEE Aerosp. Electron. Syst. 20 (3) (2005) 8–14.
[13] A. Hiliuta, R. Landry, F. Gagnon, Fuzzy corrections in a GPS/INS hybrid navigation system, IEEE Trans. Aerosp. Electron. Syst. 2 (2) (2004) 591–600.
[14] M.M. Reda Taha, A. Noureldin, N. El-Sheimy, Improving INS/GPS positioning accuracy during GPS outages using fuzzy Logic, in: Proceedings of the 16th International Technical Meeting of the Satellite Division of the Institute of Navigation ION GPS/GNSS 2003, September 9–12, Oregon Convention Center, Portland, Oregon, 2003.
[15] C.M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, New York, 1995.
[16] S. Haykin, Neural Networks – A Comprehensive Foundation, IEEE Press, 1994.
[17] A. Noureldin, T. Karamat, M. Eberts, A. El-Shafie, Performance enhancement of MEMS based INS/GPS integration for low cost navigation applications, IEEE Trans. Veh. Technol. 58 (3) (2009) 1077–1096.
[18] R. Sharaf, M. Tarbouchi, A. El-Shafie, A. Noureldin, Real-time implementation of INS/GPS data fusion utilizing adaptive neuro-fuzzy inference system, in: Proceedings of the Institute of Navigation National Technical Meeting – ION NTM 05, January 24–26, San Diego, CA, 2005.
[19] A. Noureldin, A. El-Shafie, M.R. Taha, Optimizing neuro-fuzzy modules for data fusion of vehicular navigation systems using temporal cross-validation, Eng. Appl. Artif. Intell. 20 (1) (2007) 49–61.
[20] L. Semeniuk, A. Noureldin, Bridging GPS outages using neural network estimates of INS position and velocity errors, Meas. Sci. Technol. 17 (9) (2006) 2783–2798.
[21] S. Amari, N. Murata, K.-R. Műller, M. Finke, H.H. Yang, Asymptotic statistical theory of overtraining and cross-validation, IEEE Trans. Neural Network 8 (5) (1997) 7–9.
[22] E.H. Shin, N. El-Sheimy, 2004 Aided Inertial Navigation system (AINS™) Toolbox for MatLAB® Software, INS/GPS Integration Software, Mobile Multi-Sensor Systems Research Group, University of Calgary, Calgary, Canada.