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GPS-based Land Vehicle Navigation System Assisted by a Low-Cost Gyro-Free INS Using Neural Network

Jau-Hsiung Wang and Yang Gao

(*Department of Geomatics Engineering, The University of Calgary*)
(Email: gao@geomatics.ucalgary.ca)

GPS-based land vehicle navigation systems are subject to signal fading in urban areas and require aid from other enabling sensors. A low-cost gyro-free inertial navigation system (INS) without accumulated attitude errors and complicated initializations could be an effective solution to the problem. This paper investigates a Constrained Navigation Algorithm (CNA) and the Artificial Neural Network (ANN) technique to compensate velocity output from a gyro-free INS. The vehicle's heading will be calibrated by a full circle test so that the magnetometer's bias and scale factor error could be removed. Experiments with a vehicle driven over level terrain have been conducted to assess the performance of the compensated gyro-free INS solutions. The effect of the architecture of Neural Network on prediction performance has also been discussed as well as the applicability of the proposed solution to land vehicle navigation with GPS outages.

KEY WORDS

1. GPS. 2. Gyro-Free INS. 3. Integration. 4. Neural Network.

1. INTRODUCTION.

The Global Positioning System (GPS), which is able to provide position solutions not only cost-effectively but also with long-term accuracy and availability, has found wide applications in land vehicle navigation. GPS solutions however are subject to severe degradation in the presence of signal blockage, interference and multipath since GPS observations are range measurements of line-of-sight between the GPS satellites and receivers (Parkinson 1996). Thus, GPS-based navigation systems require aids from other enabling sensors especially in urban areas. Inertial Navigation Systems (INS), based on dead-reckoning methodology to obtain the position state and with operational characteristics complementary to GPS, have been widely integrated with GPS. However, the high cost and large size of precise INS has prevented it from wide application in the automobile market. With the advent of MEMS (Micro-Electro-Mechanical System) technology, the low-cost and small-size accelerometers and gyroscopes are suitable for vehicular navigation (Anderson 2001) (Park 2002). Unlike MEMS accelerometers with more stable performance, the MEMS gyroscopes are currently still limited due to high gyro drifts and the complex initial alignment procedures for attitude determination (Kourepenis 1998). The accumulated attitude error due to gyro bias and drift would also cause significant position errors (Titterton 1997) (El-Sheimy 2003). In contrast to a gyro, a magnetometer capable of providing absolute heading information relative to magnetic north without time-accumulated errors can be combined with accelerometers to provide a navigation solution (Honeywell Inc. 2002).

A low-cost gyro-free navigation system, composed of a MEMS accelerometer and a magnetometer, can satisfy the requirements of low cost, small size and convenience-of-use for land vehicle navigation. Measurements from such a system however still contains errors such as bias, noise and disturbance which need attention before a satisfactory position solution can be derived. For example, the magnetometer measurement will be distorted by local magnetic field and external interference (Crossbow Inc. 2002) while the accelerometer measurement contains the effect of gravity field which needs to be removed by correct tilt information (El-Sheimy 2003). Although the performance of a low-cost gyro-free navigation system can be improved by some restrictions and smoothing methods, it is not sufficient for land vehicle application (Collin 2002). Advanced error compensation algorithms therefore need to be developed in order to further improve the accuracy of a low-cost gyro-free INS system.

Artificial Neural Network (ANN) is a parallel-distributed processor that allows the modelling of highly complex and nonlinear problems with a high stochastic level that cannot be solved using conventional algorithmic approaches (Noureldin 2003). ANN, a powerful tool for nonlinear input-output mapping, has been used to integrate DGPS and INS to reduce the navigation errors of INS during GPS outages (Noureldin 2003) (Chiang 2003). For a low-cost sensor with relatively high instrument noise and an uncertain measurement model, ANN is an adaptable approach to deal with its navigation errors and is more powerful than conventional approaches.

This paper integrates a low-cost gyro-free INS and GPS system for land vehicle navigation using Neural Network. Constraints on the motion of the land vehicle are first applied to derive a navigation equation to reduce navigation errors. ANN is then designed to model the nonlinear relationship between the vehicle dynamics and the navigation state errors. When GPS is available, ANN is continuously trained to model the behaviour of the navigation state errors. During a GPS outage, the pre-trained ANN is used to predict the navigation state errors to compensate the inertial navigation solution.

The remainder of the paper is organized as follows. Section 2 describes the basic and the error source of a gyro-free INS. Section 3 describes the constrained navigation algorithm and Section 4 describes the design of ANN. Section 5 presents the test results and discussions. The conclusions are in Section 6.

2. GYRO-FREE INERTIAL NAVIGATION SYSTEM.

In inertial navigation systems, gyroscopes can provide attitude updating to establish the transformation between the body frame (sensor-mounted coordinate system) and the navigation frame (local level frame). After that, the measured accelerations can be rotated to the navigation frame by the transformation to derive velocity and coordinate solutions. For a gyro-free approach, by utilizing information from magnetometers and accelerometers, it is possible to resolve this transformation since the

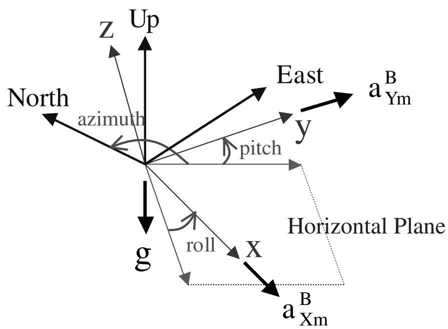

Figure 1. A Gyro-Free Approach for 2D Vehicular Navigation.

measurements on the earth's magnetic and gravity fields are able to determine the attitude of the system. Figure 1 shows a gyro-free approach for 2D vehicular navigation. The magnetometers and accelerometers are mounted in the body frame fixed to the vehicle where x-axis presents the lateral direction, y-axis the forward direction, and z-axis the vertical direction.

Considering 2D motion and neglecting the Coriolis acceleration terms, accelerometer outputs in body frame include the acceleration resulted from the motion and gravity acceleration:

$$a^B_{Xo} = a^B_{Xm} - g\sin(r) \tag{1}$$

$$a^B_{Yo} = a^B_{Ym} - g\sin(p) \tag{2}$$

where g is the gravity acceleration, r is the roll angle and p is the pitch angle. The superscript B of the acceleration refers to the body frame coordinate system. The subscript x and y refer to the acceleration component in x-axis and y-axis, respectively. The subscript o indicates the accelerometer output while the subscript m refers to the acceleration from the motion. By a coordinate transformation, the acceleration derived from the motion in a local level frame can be obtained as follows:

$$\bar{a}^L = R^L_B \bar{a}^B \tag{3}$$

where $\bar{a}^L = \begin{bmatrix} a^L_{Em} \\ a^L_{Nm} \end{bmatrix}$ and $\bar{a}^B = \begin{bmatrix} a^B_{Xm} \\ a^B_{Ym} \end{bmatrix}$.

R^L_B, the coordinate transformation matrix between the body frame (subscript B) and the local-level frame (superscript L), can be directly determined by attitude information as follows:

$$R^L_B = \begin{bmatrix} \cos(A) & \sin(A) \\ -\sin(A) & \cos(A) \end{bmatrix} \begin{bmatrix} \cos(r) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \cos(p) \end{bmatrix} \tag{4}$$

In a gyro-free INS, the azimuth A (the angle between the north and the vehicle moving direction) can be determined by magnetometers. The roll and pitch angle can be derived by measuring gravity fields. After time integration of $\bar{a}^L$, the velocity and coordinate solution in the local level frame can be obtained. However, in practice both magnetic and gravity field measurements are distorted. The magnetometer measurements are subject to the effects of nearby ferrous materials. In addition, the declination angle varying with locations should be applied to adjust magnetic north to true north. Since in land vehicle applications the environmental magnetic field generated by the vehicle itself has a weak time-variant characteristic and the declination angle can be considered as constant in a small area, a full circle test can be applied to remove the bias and scale errors of the compass heading.

In equations (1) and (2), accelerometer outputs include the motion acceleration and gravity acceleration where the former is of interest to us. In order to extract the motion acceleration from the accelerometer outputs, the tilt information must be solved first. In the static mode, the accelerometer outputs contain only the local gravity acceleration. By projecting the local gravity acceleration to the x and y directions, the roll and pitch information can be derived from the accelerometer measurements a^B_{Xo} and a^B_{Yo} respectively (El-Sheimy 2003):

$$roll = \sin^{-1}(a^B_{Xo}/g) \tag{5}$$

$$pitch = \sin^{-1}(a^B_{Yo}/g) \tag{6}$$

The roll and pitch accuracy are dependent on the accelerometer accuracy which is mainly governed by the accelerometer bias. For example, a 10 mg accelerometer bias will result in a roll/pitch error of 0·57 degrees. While the vehicle is moving, the accelerometer senses not only the gravity acceleration but also the motion acceleration. As a result, the estimation of the tilt information cannot be achieved. One-degree tilt error, corresponding to 18 mg acceleration error, will result in 317·844 m of position error after one-minute integration. In this case, using other available information such as zero acceleration update or GPS-based acceleration is required in order to distinguish the gravity acceleration from the motion acceleration (Collin 2002).

3. A CONSTRAINED NAVIGATION ALGORITHM.

For land vehicle navigation the nature of vehicle dynamics, if known, can provide extra information as constraints to reduce the navigation errors. The constraints on the motion of the land vehicles can be defined as follows (Brandt 1998):

(a) The direction of the vehicle's velocity coincides with the direction of the vehicle's forward axis.
(b) The pitch and roll angles of the vehicle's body relative to the Earth surface are very small (mostly in urban area).
(c) Vehicle always remains on the Earth surface.

With the above constraints, the navigation equations can be written as follows:

$$\frac{dV^B}{dt} = a^B_{Yo} \tag{7}$$

$$V^L_E = V^B \cos(A) \tag{8}$$

$$V^L_N = V^B \sin(A) \tag{9}$$

where α^B_{Yo} is the accelerometer outputs in the vehicle forward direction, V^B is the vehicle velocity, A is the azimuth angle, V^L_E and V^L_N are the projected vehicle velocities

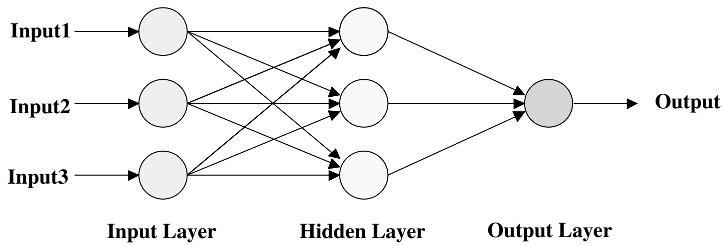

Figure 2. Multi-layer Feed-Forward NN Architecture.

in the east and north directions, respectively. Thus, a low-cost gyro-free navigation system is able to provide the required measurements based on the above navigation equations where the position errors are mainly due to vehicle heading and velocity errors. The vehicle heading errors, including both bias and scale factor errors in the magnetometer, can be calibrated by the full circle test. The velocity errors are the time integrations of the forward acceleration errors derived from the bias, scale factor, and gravity field effects. In this paper, Neural Network will be applied to model and compensate the vehicle velocity errors in the gyro-free INS system.

4. DESIGN OF NEURAL NETWORK FOR ERROR COMPENSATION.

ANN resembles the human brain by using the inter-neuron connections weights to store knowledge which is acquired through a learning process. ANN can be trained to solve problems such as a nonlinear input-output mapping problem that are difficult for conventional computers or human beings (Noureldin 2003).

A multi-layer feed-forward Neural Network (NN) architecture is shown in Figure 2. The input layer accepts the inputs and distributes them to the next layer of processing elements. The neurons in the next layer gather values from all input neurons and pass the net input to an activation function that calculates the output for each node. This procedure repeats for each layer until the output layer. Denote the connection weight between the i-th neuron in the $(k-1)$-th layer and the j-th neuron in the k-th layer as $W_{ij}^{(k-1)}$ and the output, activation function, and the threshold of the j-th neuron in the k-th layer as $y_j^{(k)}, f_j^{(k)}(\cdot)$, and $\theta_j^{(k)}$, respectively. If the number of the neurons in the k-th layer is N_k and the number of the layers including the input and output layer is M, the input-output relationship for each neuron can be described as:

$$y_j^{(k)} = f_j^{(k)}\left(\sum_{i=1}^{N_{k-1}} W_{ji}^{(k-1)} y_i^{(k-1)} - \theta_j^{(k)}\right) \tag{10}$$

where $j=1, 2, \ldots, N_k$; $k=1, 2, \ldots, M$.
In this paper, a nonlinear sigmoid (logsig) activation function defined in the following is utilized to provide the nonlinearities.

$$f(v) = \frac{1}{1+\exp(-\alpha v)} \tag{11}$$

where α is the slope parameter. Thus, the outputs of the network, $y_1^{(M)}, y_2^{(M)}, \ldots, y_{N_M}^{(M)}$ are the nonlinear combination of network inputs, all of the prior neurons' outputs and parameters.

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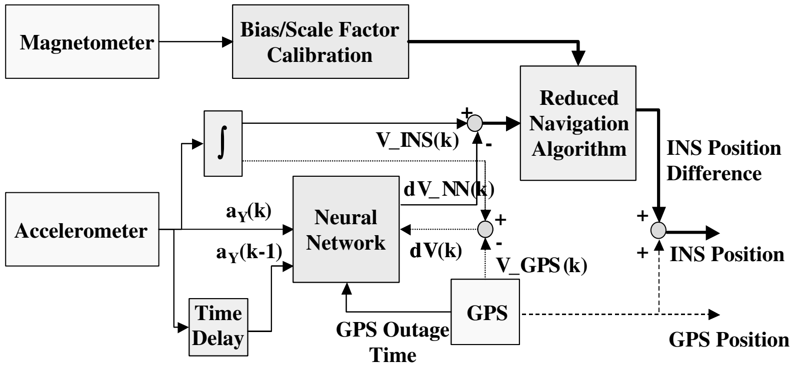

Figure 3. Configuration of Proposed Architecture for Error Compensation.

A supervised learning process can then be utilized to develop the correct association by adjusting the parameters in equation (10). The parameters of NN are updated by iteratively comparing the output of NN with target until the error between NN output and target is lower than a predefined criterion. The typical update scheme is a back-propagation process that calculates the error between the NN output and the target and propagates it in the backward direction through the network (Noureldin 2003).

It should be noted that a successful application of ANN requires the selection of an appropriate architecture to specify the number and organization of the processing elements (neurons). In general, the optimal architecture is empirically chosen.

In this paper, a three-layer feed-forward NN with a back-propagation learning algorithm has been developed to estimate the vehicle velocity errors. Since the vehicle velocity is the time integration of the forward acceleration and the velocity errors depend on the vehicle dynamic, the previous and present y-axis accelerometer outputs and the integration time are chosen as the NN input while the vehicle velocity errors as the NN output. When GPS is available, the vehicle velocity errors are derived from differencing the velocities from GPS and gyro-free INS. NN is continuously trained to model the relationship between inputs and output. During a GPS outage, the pre-trained NN is used to predict the vehicle velocity errors that would subsequently be applied to correct the velocity solution derived from the gyro-free INS system. Based on the navigation equations given in equations (7) to (9), the gyro-free navigation solution is calculated from the calibrated magnetometer measurements and NN-compensated vehicle velocity. The configuration of the proposed architecture for error compensation of a low-cost gyro-free inertial navigation system is shown in Figure 3.

5. TEST RESULTS AND DISCUSSIONS.

A field test was conducted to assess the performance of the proposed architecture. A laptop was used to log data from a Honeywell-HMR3300 digital compass accompanying with a build-in 2-axis ADXL202E MEMS accelerometer, and a GPS receiver through two serial ports. The digital compass was run at a sampling rate of 10 Hz. The GPS receiver used was a high precision type (JAVAD-Legacy) in order to establish reference for the test and it was operated in a Standard Positioning Service (SPS) mode during the test period with a sampling rate of 1 Hz. GPS errors are very small (~5 m) compared to the low-cost gyro-free INS solution (~100 m). A data acquisition program was developed to log data tagged using the computer time. After the 10 Hz inertial data was averaged to 1 Hz data, all sensor data was aligned with GPS time based the computer time frame.

In the constrained navigation algorithm, we have assumed the tilt angle is zero. But in practice, there still exists small tilts even over level terrain. In order to remove this effect, two runs of tests on the same route, both having a time period of about 460 seconds, were performed. The first run was used to train NN and the second run to verify the performance of the proposed architecture. In order to evaluate the effect of NN architecture, we also designed three different NNs to process the same data set. The first one (NN1) had 6 neurons, the second one (NN2) had 12 neurons, and the third one (NN3) had 27 neurons in hidden layer. While processing data of the first run test, NN1 took 50 training epochs to achieve the training error of 0·02 m/s, NN2 took 120 training epochs to achieve the training error of 0·0056 m/s, and NN3 took 164 training epochs to achieve the training error of 0·00098 m/s. In the second run test, vehicle velocity error was predicted by the pre-trained NN1, NN2, and NN3 as shown in Figure 4, Figure 5, and Figure 6 respectively. The reference of the vehicle velocity error was calculated by GPS. The results demonstrate that the velocity error of the low-cost gyro-free INS is correlated with vehicle dynamic and integration time. In addition, NN2 can predict vehicle velocity error more accurately than NN1 and NN3 because NN2 has a more appropriate number of neurons in the hidden layers which gave more proper nonlinearities to model the input-output relationship. It should be noted that, a too simple NN cannot provide adequate nonlinearities and a too complicated NN compared to the complexity of the targeted system could result in an over-fitting problem.

Figure 7, Figure 8 and Figure 9 illustrate the prediction accuracy of NN1, NN2, and NN3 respectively. The root mean square (RMS) and mean value of the prediction errors are 1·2763 and −0·0987 (m/s) for NN1 and 1·0062 and −0·0655 (m/s) for NN2 and 1·712 and −0·238 (m/s) for NN3. It means that NN2 with more adequate structure can provide better performance.

For the error compensation of vehicle heading, based on the result of full circle test, the bias and scale factor errors of the magnetometer can be calibrated directly. Figure 10 shows both the uncalibrated and calibrated heading information as well as GPS heading information in the second run of test. The magnetic disturbance has not been considered in this test but it should be filtered out.

Following the constrained navigation algorithm (CNA), the coordinate solution of a low-cost gyro-free INS can be obtained from the calibrated heading information and NN-compensated vehicle velocity. The vehicle trajectories of the second run from GPS and the compensated low-cost gyro-free system are shown in Figure 11. The distance between gyro-free INS and GPS position in each epoch is calculated as the horizontal position error. The horizontal position error can be significantly reduced by the proposed architecture, from about a kilometre to the order of a hundred-metres after a time integration of 460 seconds. Figure 12 illustrates the performance of a compensated low-cost gyro-free INS in the position domain. The maximum horizontal position error is reduced to 146·6, 136·9, and 180·8 metres while NN1, NN2, and NN3 are applied to predict the vehicle velocity error respectively, i.e., with

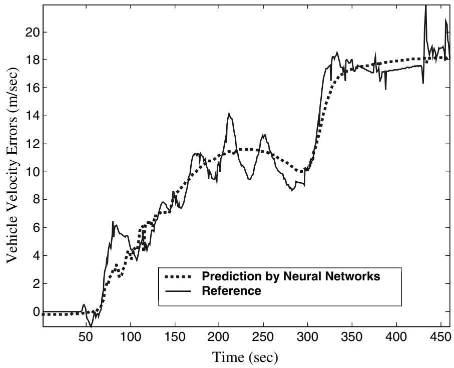

Figure 4. Performance of NN1.

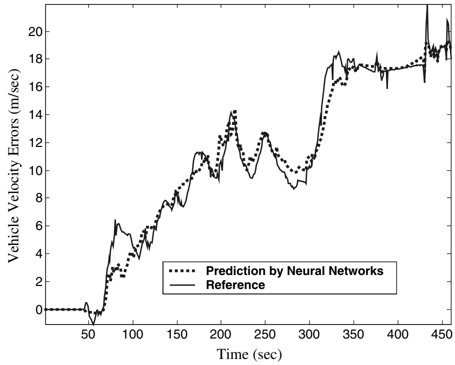

Figure 5. Performance of NN2.

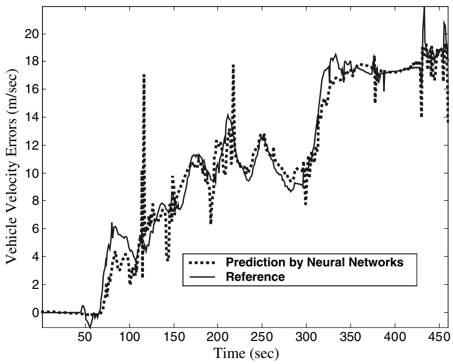

Figure 6. Performance of NN3.

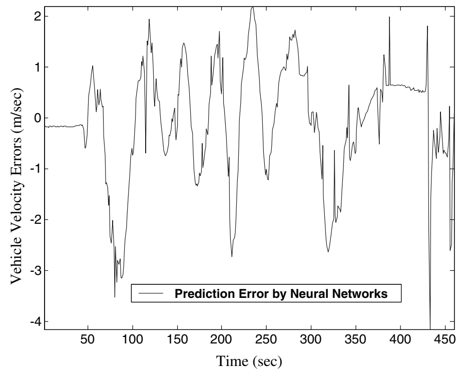

Figure 7. Prediction Error by NN1.

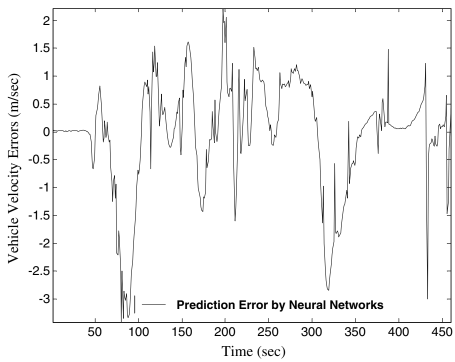

Figure 8. Prediction Error by NN2.

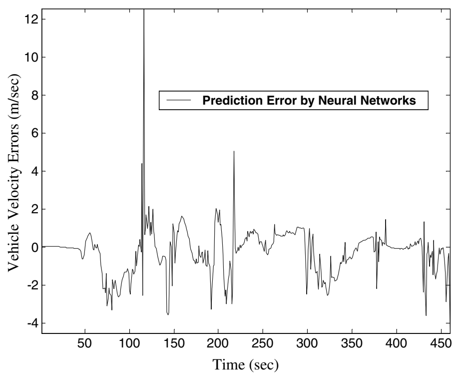

Figure 9. Prediction Error by NN3.

460 seconds GPS outage, the horizontal position error of the compensated low-cost gyro-free system is under about 180 metres.

In order to investigate the applicability of the proposed gyro-free INS for land vehicle navigation, more frequent GPS solutions are used to update the position,

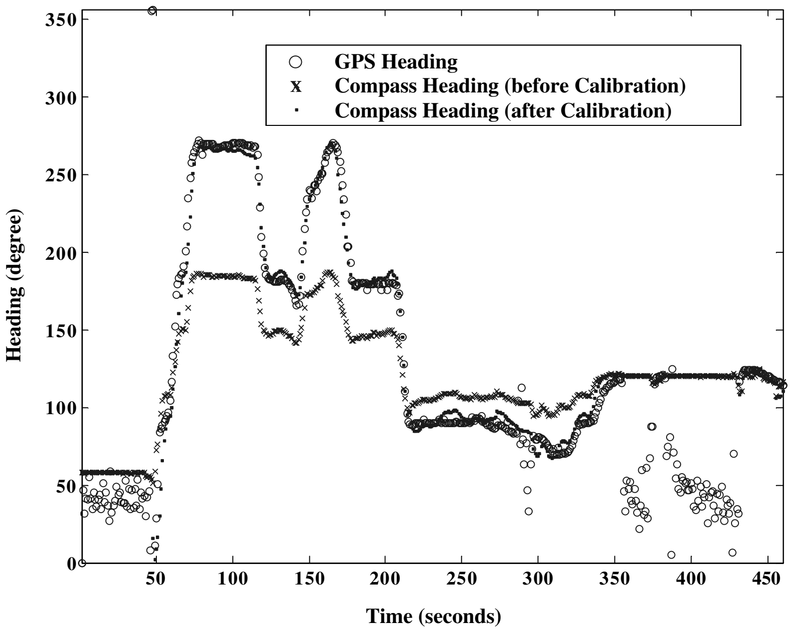

Figure 10. Calibrated Heading Information.

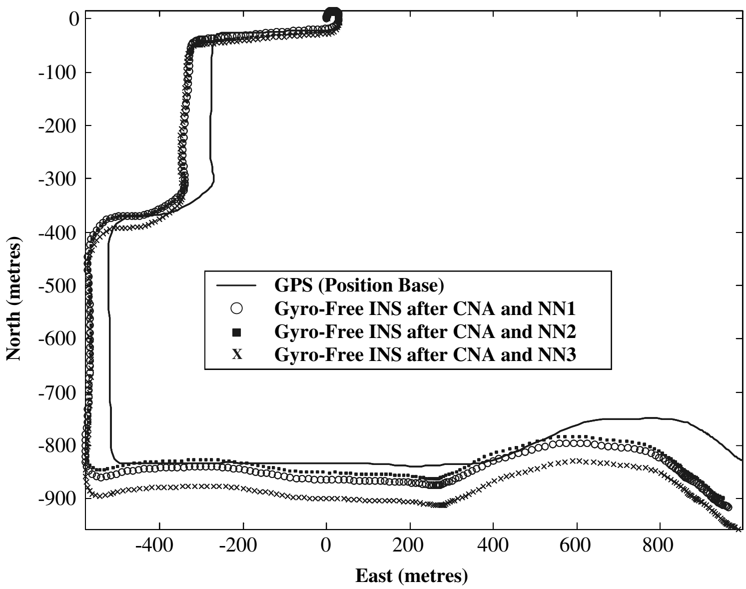

Figure 11. Vehicle Trajectories.

velocity, and heading information. Considering the use of NN2 to predict the vehicle velocity error, Figure 13 shows the horizontal position errors when 60, 45 and 30-second periods of GPS outage are simulated. The maximum and root mean square (RMS) values of the position errors are summarized in Table 1. When GPS outage

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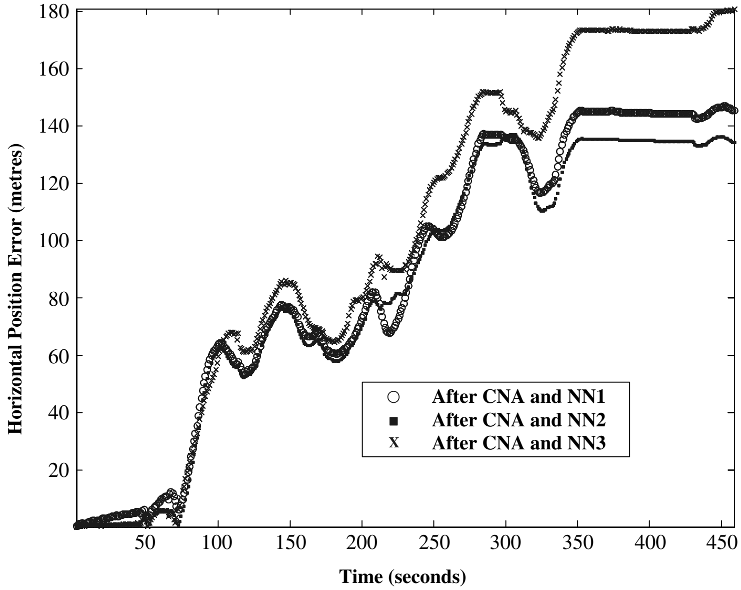

Figure 12. Horizontal Position Error.

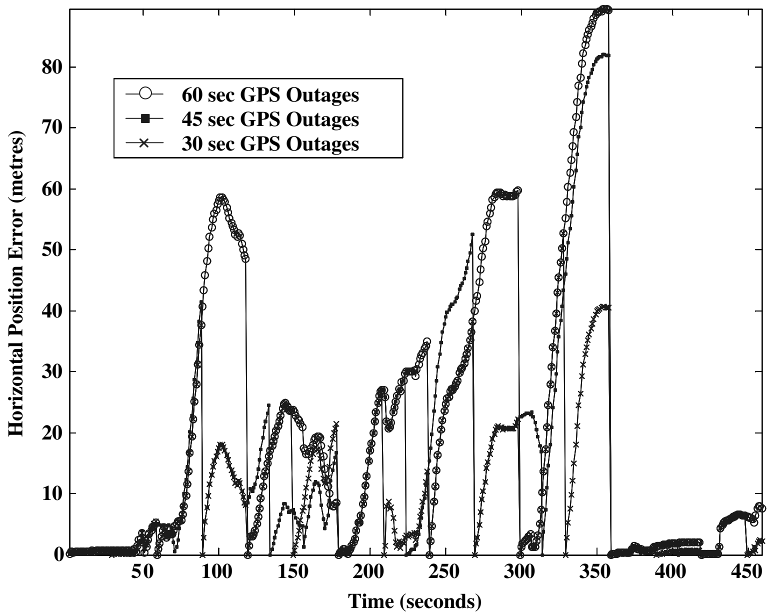

Figure 13. Position Errors with Different GPS Outages.

is less than 45 seconds, the RMS value of position errors is below 24·20 metres, satisfactory for route finding in land vehicle navigation. When GPS outage is less than 30 seconds, the compensated low-cost gyro-free solution with 15·58 metres (RMS) position error can assist a GPS-based navigation system in location service.

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Table 1. Position Errors with Different GPS Outages.

GPS Outage (s)	Maximum (m)	RMS (m)
60	89·58	31·85
45	82·04	24·20
30	52·69	15·58

To extend the application with a higher accuracy demand, longer GPS signal outage or over more tugged terrain, further research is needed to improve the error compensation.

6. CONCLUSIONS.

In this paper we have discussed the use of a low-cost gyro-free inertial navigation system to assist GPS-based land vehicle navigation. A constrained navigation algorithm has been proposed to reduce the errors. Vehicle heading provided by a magnetometer was calibrated by a full circle test. The vehicle velocity obtained from the time integration of the measurements of a forward accelerometer, was compensated by a pre-trained Neural Network describing the association between the input (accelerometer measurement and integration time) and the output (velocity error). The architecture of the Neural Network (the number and organization of the processing neurons) which will influence the prediction performance was also discussed.

The test result demonstrated that the compensated low-cost gyro-free INS can be utilized to assist GPS-based land vehicle navigation while the vehicle is driven on level terrain. The performance is inversely proportional to the length of the GPS outages. For further research, the tilt information needs to be included for more accurate modelling of the vehicle velocity errors. The magnetic disturbance also requires to be filtered out for more reliable determination of the vehicle heading.

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