NEURAL NETWORK AIDED KALMAN FILTERING FOR INTEGRATED GPS/INS GEO-REFERENCING PLATFORM

Jianguo Jack Wang [a, *], Jinling Wang [a], David Sinclair [b], Leo Watts [b]

[a] School of Surveying and Spatial Information Systems, UNSW, Sydney, NSW 2052, Australia
jianguo.wang@student.unsw.edu.au, Jinling.Wang@unsw.edu.au
[b] QASCO Surveys Pty. Limited, 41 Boundary St. South Brisbane, Qld, 4101, Australia

KEY WORDS: Neural network, GPS, INS, Kalman filter, Georeferencing, Prediction

ABSTRACT:

Kalman filtering theory plays an important role in integrated GPS/INS georeference system design. A Kalman filter (KF) uses measurement updates to correct system states error and to limit the errors in navigation solutions. However, only when the system dynamic and measurement models are correctly defined, and the noise statistics for the process are completely known, a KF can optimally estimate a system's states. Without measurement updates, a Kalman filter's prediction diverges; therefore the performance of an integrated GPS/INS georeference system may degrade rapidly when GPS signals are unavailable. It is a challenge to deal with this problem in real time though it can be handled in post processing by smoothing methods.
This paper presents a neural network (NN) aided Kalman filtering method to improve navigation solutions of integrated GPS/INS georeference system. It is known that the errors inherent to strapdown inertial sensors are affected by the platform manoeuvre and environment conditions etc., which are hard to be modelled precisely. On the other hand, NNs have the capability to map input-output relationships of a system without apriori knowledge about them. A properly designed NN is able to learn and extract complex relationships given enough training. Furthermore, it is able to adapt to the change of sensors and dynamic platforms. In the proposed loosely coupled GPS/INS georeference system, an extended KF (EKF) estimates the INS measurement errors, plus position, velocity and attitude errors, and provides precise navigation solutions while GPS signals are available. At the same time, a multi-layer NN is trained to map the vehicle manoeuvre with INS prediction errors during each GPS epoch, which is the input of the EKF. During GPS signal blockages, the NN can be used to predict the INS errors for EKF measurement updates, and in this way to improve navigation solutions. The principle of this hybrid method and the NN design are presented. Land vehicle based field test data are processed to evaluate the performance of the proposed method.

1. INTRODUCTION

1.1 Geo-referencing using GPS and INS

Geo-referencing mobile mapping and remote sensing platform is always a challenge considering its requirement for accuracy, reliability operation environment. With the development of GPS and INS technologies in recent decades, it is an increasing trend in the use of integrated GPS and INS systems for platform geo-referencing. GPS is capable of providing accurate position and velocity information if at least four GPS satellites with good geometry are directly viewable by a GPS antenna. On the other hand, attitude information can not be obtained from GPS measurements though multi-antenna can provide it with limited accuracy. Furthermore, satellite signals are easily to be blocked, especially for land vehicle, which worsens the GPS positioning accuracy and even makes it unusable.

INS is a self-contained system, incorporating three orthogonal accelerometers and gyroscopes to measure linear acceleration and angular rates in three directions respectively. A set of mechanization equation is applied to the raw measurements from the sensors to calculate position, velocity and attitude information. The INS inertial sensors have inherent errors, which can cause a significant degradation of INS performance over a period of time. Especially for strapdown INS (SINS), in which inertial sensors are subjected to the full range of heading and attitude changes and turn rates which the vehicle experiences along its path. Therefore, GPS and INS are often integrated together to overcome the drawbacks associated with each system.

1.2 GPS/INS Integration Techniques

GPS and INS are usually integrated with a KF to overcome drawbacks associated with each system, and provide a robust navigation solution. Since GPS has a consistent, long-term accuracy, it is used to correct INS measurements and thus to prevent the long-term growth of their errors. On the other hand, the accurate short-term measurement provided by the INS is used to solve problems related to GPS such as cycle slips and clock biases. KF is the optimal filter for modelled processes, and the core of most GPS/SINS integrated systems implemented to date (Farrell and Barth, 1999). It can optimally estimate the position, velocity and attitude of a moving vehicle using precise GPS measurements to update the filter states. KF is computationally efficient, which is especially useful for real-time applications. With correct dynamic models and stochastic models of GPS and INS errors, KF can produce very accurate geo-referencing solutions provided that there is a continuous access to GPS signals. If GPS outages occur, KF operates in prediction mode, and corrects INS measurements based on the system error model.

* Corresponding author.

There are three types of GPS/INS integration, namely loosely, tightly and ultra-tightly coupled, which are categorized by the level of measurements in each subsystem used for the integration. Figure 1 is the block diagram of a typical loosely coupled GPS/INS integration system using KF.

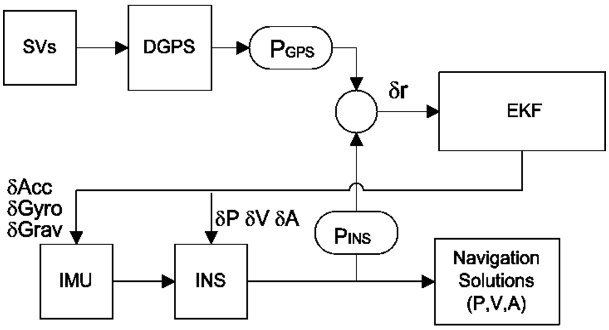

Figure 1. A typical DGPS/SINS integration with KF

There are several considerable drawbacks of KF. The necessity of accurate stochastic modelling may not be possible in the case of low cost and tactical grade sensors. It is demanding to accurately determine the parameters of the system and measurement covariance matrices for each new sensor. The weak observability of some error states may lead to unstable estimates of the error states. And inherently, KF has relatively poor accuracy during long GPS outages, since in most cases a first order Gauss Markov assumption is made which means that the current estimates depend solely on the previous estimates. So if the previous estimates have any errors, these errors will be propagated into the current estimates and will be summed with new errors to accumulate an even larger errors (Goodall et al., 2005).

Many algorithms are proposed to overcome the limitations of the KF mentioned above. Various adaptive KF algorithms have been developed to eliminate the requirement of accurate stochastic modelling and pre-resolved parameters of the system and measurement covariance matrices for each new sensor (filter tuning). Some artificial intelligence methods, such as NN and fuzzy logic reasoning etc., are also proposed for this purpose.

NNs have been proposed as a multi-sensor integrator (Chiang and El-Sheimy, 2004; El-Sheimy and Abdel-Hamid, 2004). It is well known that NNs are capable of mapping input-output relationships. This means that no initial dynamic or noise models need to be set as these are learned over time. NNs can also adapt to the changes of the system model or vehicle dynamic. At the same time, however, the NN approach also has some shortcomings. Its accuracy is not ideal and depends on the artificial experience. At current stage, therefore, Kalman Filter still remains at the forefront of GPS/SINS integration.

1.3 Neural Network Aided Kalman Filtering

Combining KF with NN to outwit their inherent shortcomings and improve the overall performances of GPS/SINS integrated systems is a potential solution. A NN aided adaptive EKF was proposed by Jwo and Huang (Jwo and Huang, 2004). A NN based approach for tuning KF was developed by Korniyenko et al (Korniyenko et al., 2005). NN and KF were combined together to bridge GPS outages (Goodall et al., 2005; Kaygisiz et al., 2004; Semeniuk and Noureldin, 2006). NN model was used for de-noising MEMS-based inertial data (El-Rabbany and El-Diasty, 2004). NN is also employed to map the platform dynamic with corresponding Kalman filter states to smooth system outputs and to bridge GPS outages (Wang et al., 2006a; Wang et al., 2006b).

A new EKF and NN hybrid method is introduced in this paper to improve the performance of integrated DGPS/SINS systems during GPS outages, by employing NN to estimate GPS corrections. A radial based function NN (RBFNN) is trained to map these input-output relationships along with the EKF measurement update. The inputs of the NN are the parameters representing vehicle dynamic situation and variations, and the outputs are the INS positioning errors corrected by the GPS. When no GPS measurements are available, the outputs of the trained NN are used to estimate INS positioning errors and improve navigation solutions.

This paper is organized as follows. The INS error estimation in EKF during the filter prediction is analyzed in Section 2. The relation between the vehicle dynamic variation and the filter error states is explored. The combination of NN and EKF is introduced in Section 3. The inputs and outputs of a NN are defined. Pre-processing is conducted for NN inputs in order to establish better input-output relationships. The design and operation of the NN are introduced in Section 4. Section 5 presents field tests and discusses the results. The concluding remarks are given in Section 6.

2. INS ERROR ANALYSIS

In fact any lack of precision in a measurement used in a dead reckoning system such as SINS is passed from one estimate to the next with the overall uncertainty in the precision of the calculated navigation solution drifting with time. In integrated DGPS/SINS system, the SINS estimation error just accumulates during the gaps of GPS measurements. The error is frequently corrected by GPS measurement so that the accuracy of navigation solution can be

The performance of SINS is highly dependent on the motion of the host vehicle. Strapdown inertial sensors are subjected to the full range of heading and attitude changes and turn rates as the platform experienced. This is in marked contrast to the inertial sensors in a stable platform navigation system which remains nominally fixed in the chosen reference frame and are not subjected to the rotational motion dynamics of the vehicle (Titterton and Weston, 2004). The need to operate in a relatively harsh dynamic environment whilst being able to measure large changes in vehicle attitude with sufficient accuracy has a major effect on the choice of inertial sensors. For example, gyroscope scale-factor accuracy and cross-coupling must be specified more precisely in a SINS than it would be necessary for a platform system of comparable performance. In addition, a number of motion dependent error effects need to be taken into account, including inaccuracies introduced through cyclic or vibratory motion of the host vehicle, which are hardly to model.

Figure 2 is the example of INS prediction errors during GPS epochs in an integrated system using EKF with field test data. The error is presented by the positioning difference between a SINS and differential GPS (DGPD). The lower figure is the corresponding vehicle manoeuvre presented by acceleration measurements, which will be selected as part of the NN input.

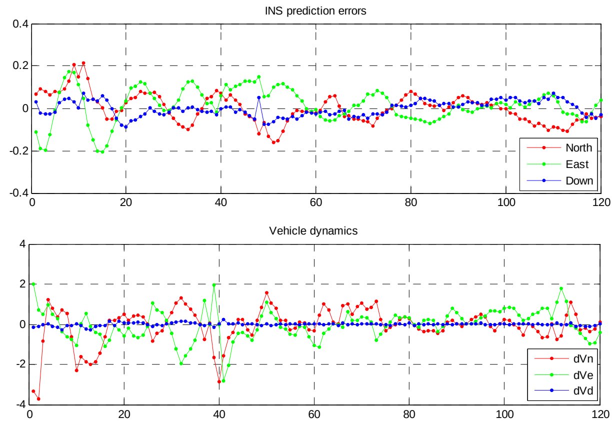

Figure 2. INS prediction errors and vehicle manoeuvre

It is noted from the above figure that INS prediction errors are not random noise; instead, they have certain patterns that could be related to the vehicle manoeuvres, especially the errors in the horizontal directions. It is a challenge, however, to find a proper method to map the relationship and to estimate INS prediction errors during GPS outages. Here NNs are employed to map the relationship between the INS prediction errors and the vehicle manoeuvre.

3. SYSTEM DESIGN

3.1 NN and EKF Combination

The block diagram of proposed EKF and NN hybrid system is presented in Figure 3 and Figure 4, for NN training phase and prediction phase respectively. The vehicle manoeuvre derived from navigation solutions are continuously input into the NN. As long as the DGPD signal is available, the system operates in the training phase. The EKF produces navigation solutions and updates the filter states with GPS measurements. At the same time, EKF measurement δr, the INS positioning error with respect to GPS measurement, is selected as the target/output for the NN. The training process matches the NN output with the target incessantly by adjusting the parameters in the NN at each epoch of EKF measurement update, as shown in Figure 3.

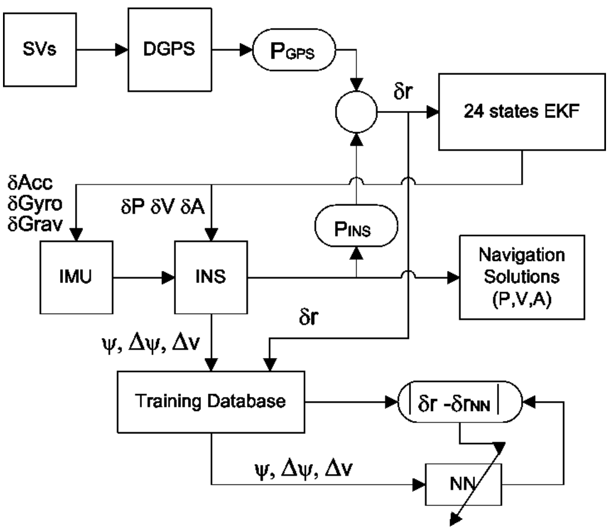

Figure 3. System diagram during NN training phase

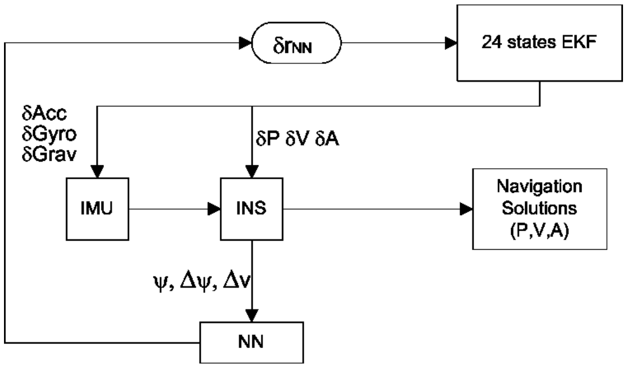

Figure 4. System diagram during NN prediction phase

During GPS outages, as shown in Figure 4, no GPS signal is available. The NN output δr_{NN} is used as the EKF measurement δr to keep the EKF running as if the GPS is available for INS error compensation, if the NN is well trained. Otherwise, No EKF measurement update is conducted, the EKF keeps in prediction model as in normal EKF only case.

The principal strategy of the proposed NN and EKF hybrid method is to map the relationship between vehicle manoeuvre and the INS positioning errors during each EKF measurement update with NN. The system navigation errors during GPS outages can be effectively attenuated if INS positioning errors can be estimated. The NN training procedure is executed at the GPS sampling rate. Then the output of the well-trained NN can be used for EKF measurement update at the same rate during the GPS outages.

3.2 NN Input and Output Selection

The NN outputs, or the training targets, are selected as the INS positioning error with respect to GPS measurement, which is also the measurement of the EKF in the loosely coupled DGPS/SINS integration system. The NN inputs are expressed as follows:

$$NN_{out} = \delta r = [\delta r_N, \delta r_E, \delta r_D] \tag{1}$$

To fully represent the vehicle dynamic variation, the input parameters of the NN are selected as the changes of vehicle velocity and attitude in each epoch. The average attitude in each epoch is also selected to deal with errors relating to gravity and earth rotation etc. The NN inputs can be selected as follows:

$$\begin{aligned} NN_{in} &= [\Delta v \Delta\psi, \psi] \\ &= [\Delta v_N, \Delta v_E, \Delta v_D, \Delta\psi_H, \Delta\psi_P, \Delta\psi_R, \psi_H, \psi_P, \psi_R] \end{aligned} \tag{2}$$

It should be noticed that as the heading angler ψ_H is limited to the change between π and $-\pi$, its changing rate $\Delta\psi_H$ has spikes when the heading angle has jumps between π and $-\pi$. These jumps will disturb the NN training, and need to be removed. This kind of jumps may also happen to the pitch and roll parameters for airborne applications, where no any limit to the aeroplane manoeuvre.

After selecting proper inputs and outputs, a NN need to be designed and trained to map the relationships between them.

There are several items need to be decided in the design of a NN, such as the number of layers, the number of neurons and the transfer function of each layer, the network training algorithm, the method and goal etc.

4. NEURAL NETWORK DESIGN

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A NN can be trained to perform a particular function by adjusting the values of the connections (weights) between elements so that a particular input leads to a specific target. The NN is adjusted, based on a comparison of the output and the target, until the network output matches the target. The procedure of supervised learning for NN is shown in Figure 5(Chiang and El-Sheimy, 2004). Given an unknown model or an unknown functional relationship with its input ***x*** and observed target ***d***. A neural network learns to fit the relationship by comparing the output ***y*** from a neural network with the observed target ***d***. It then adjusts the value of its internal weighted links ***w*** iteratively until the error ***e*** between ***y*** and ***d*** meet a predefined accuracy; or after certain times iteration.

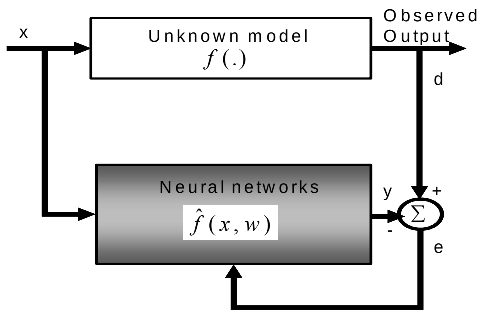

Figure 5. NN learning procedure

The learning rule specifies how the parameters in a NN should be updated to minimize a prescribed error measure, which is a mathematical expression that measures the discrepancy between the network's output and the target. Typically many such input/target pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training.

The neuron model and the architecture of a NN describe how the network transforms its input into an output. A NN can have several layers. Each layer has a weight matrix *W*, a bias vector *b*, and an output vector *a*. A three-layer network and the corresponding functions are expressed as Equation (3). The number of the layers is appended as a superscript to the variable of interest, to distinguish them between each of these layers. The network output is the function of the network input with all the function of each layer imbed together, as expressed by Equation (3).

$$\mathbf{a}^3 = \mathbf{f}^3(\mathbf{LW}^{3,2}\mathbf{f}^2(\mathbf{LW}^{2,1}\mathbf{f}^1(\mathbf{IW}^{1,1}\mathbf{p}+\mathbf{b}^1)+\mathbf{b}^2)+\mathbf{b}^3 = \mathbf{y} \tag{3}$$

Each layer of a multi-layer network plays different role. A layer that produces the network output is called an output layer. All other layers are hidden layers. The neurons in the hidden layer gather values from all input neurons and pass the input to a transfer function that calculates the output for each neural node. It is common for different layers to have different numbers of neurons. The transfer function ***f*** of each layer can be selected individually. A three-layer feed-forward NN is employed in this approach. The transfer functions of the first and second layers are sigmoid and the third layer is linear.

Table 1. The parameters of three NNs

	output	Inputs					neurons
NN_N	δr_N	Δv_N	ψ_P	ψ_R	$\Delta\psi_H$	$\Delta\psi_P$	3,3,1
NN_E	δr_E	Δv_E	ψ_P	ψ_R	$\Delta\psi_H$	$\Delta\psi_R$	3,3,1
NN_D	δr_D	Δv_D	ψ_P	ψ_R	$\Delta\psi_P$	$\Delta\psi_R$	3,6,1

Instead of using a single NN that outputs a vector of estimates, three separate NNs are used to predict the position differences in orthogonal directions. This is to avoid coupled learning during training where degradation of one output may occur while the others improve. This approach also increases the speed of convergence of the overall system by decreasing the number of neurons in each NN. This is because that one NN with three outputs and more parameters in input needs a high number of hidden layer neurons. The proposed structure exploits three NNs with relatively low numbers of neurons.

5. TEST RESULTS

Field test data were collected to evaluate the proposed hybrid method. The test system comprises two sets of Leica 530 GPS receiver and one set of Boeing's C-MIGITS II (DQI-NP) INS system, which gyro and accelerometer bias is 5 deg/hr and 500 μg respectively. A Micro Tracker GPS receiver was used to synchronize the INS time tagging with the GPS time. One of the Leica receivers was set up as a reference station and the other one used as rover receiver with its antenna next to the INS unit, above the roof of the test vehicle. 1 Hz GPS data were saved in GPS receiver PCMCIA card and 100 Hz IMU data were stored in a notebook PC. The horizontal trajectory of the test is shown in Figure 6.

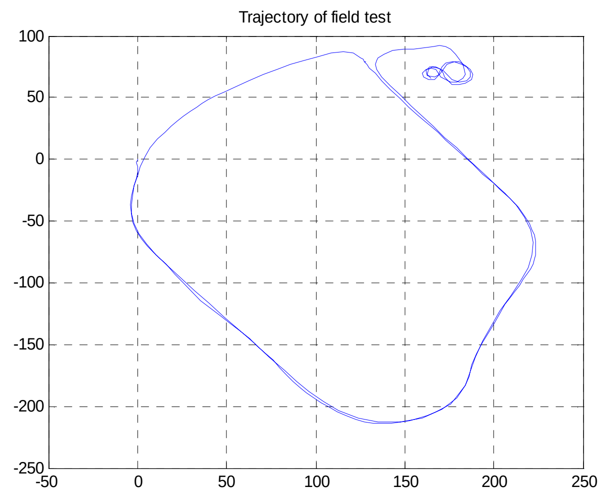

Figure 6. Horizontal trajectory of the field test

The row GPS measurement data were processed first to generate reference solutions. Then GPS and INS data were processed with the proposed algorithm to evaluate the proposed EKF and NN hybrid approach for GPS/INS integration.

5.1 NN Training Results

The NN was trained with an incremental batch method. A set of 60 epochs input vectors were applied to train the three NNs by adjusting their weight and bias matrixes. Then the next set of input vectors were applied for training. The back-propagation algorithm computes derivatives of the cost function with respect to the network weights. The weights were then updated using conjugate gradient learning algorithm. It can reduce oscillatory behaviour in the minimum search and reinforces the weight adjustment with previous successful path direction (Chiang and Nassar, 2002).

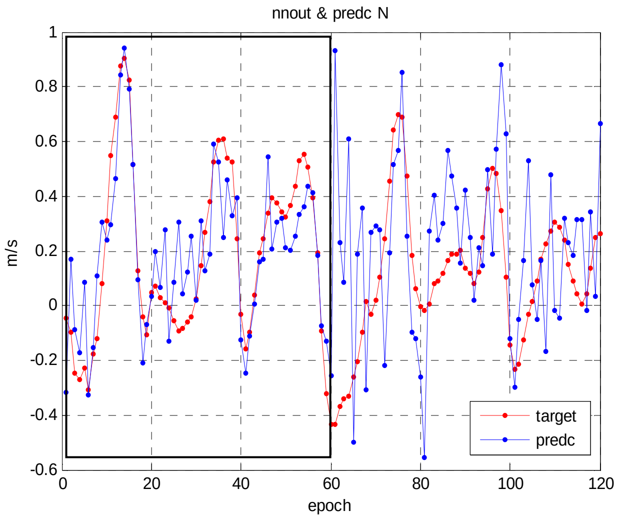

Figure 7. NN training results

The training results of two parameters with two different INS are shown in Figures 7. The NN output is very close to the target in the training window (masked in the figures), and keeps to follow the target after the window, though it is much less similar to the target in comparison with the output in the training window. This indicates that after training, NN can make reasonable prediction for quite a long period, and improve system navigation solutions during GPS signal outages. The uncertainty in measurement noise covariance matrix in the EKF during the prediction is set 5 times of the original training values. It should be noticed that different training set requires different number of neurons in a NN to achieve optimal training results.

5.2 Navigation Results

In order to access the performance of the hybrid method, GPS outages were simulated along different portions of the test trajectory. The NN was trained 60 seconds before each GPS outage, which lasts for 60 seconds. During the GPS outages, the EKF uses the output of the NN for measurements update. The hybrid navigation results are compared with the results of INS stand along navigation, in terms of position, velocity and attitude errors referencing to the case without GPS outages. The results are listed in the Table 2.

Table 2. Navigation test results

Section	δx (m)		δv (m/s)		$\delta \psi$ (sec)	
	NN	KF	NN	KF	NN	KF
1	3.5	6.8	0.10	0.23	13	33
2	2.2	5.2	0.09	0.21	15	31
3	2.4	5.3	0.11	0.22	22	41
4	2.6	6.1	0.08	0.24	23	59
5	4.1	9.7	0.16	0.36	32	81
1-NN/KF	55.2%		57.2%		56.0%	

The test results above show that the NN and KF hybrid method can improve the navigation solutions, in terms of position, velocity and attitude, during the GPS outages. The NN after training works well near the training window. Its output can make reasonable predictions after training, and correct the EKF predictions. Further research will be done to find the optimal NN architecture and an effective online training method.

6. CONCLUDING REMARKS

This paper has presented a NN and KF hybrid method to reducing KF drift during GPS outages. The inputs of the NN are selected as the measurements of the EKF in a loosely coupled DGPS/SINS integration system. The outputs of the NN are selected as the parameters representing a vehicle's dynamic variation. The NN is merged into an EKF for DGPS/SINS integration. The outputs of the trained NN are used to compensate EKF drifts and improve navigation solutions when no GPS measurements are available.

It is shown that relationships exist between a vehicle dynamic variation during the EKF measurement update (NN input) and the INS prediction error (NN output). Primary test results have shown that three-layer feed-forward NNs with back the propagation learning method is capable of mapping the complex relationships after training. The proposed method can reduce the impact of vehicle dynamic variations, and improve the navigation solution during GPS outages, by about 60%, in comparison with INS stand along results in the GPS outage of 60 seconds.

Acknowledgements

This research is supported by an ARC (Australian Research Council) research project on 'Integration of GPS/PL/INS to Geo-reference Airborne Surveying and Mapping Sensors.

REFERENCES

Chiang, K.-W. and El-Sheimy, N., 2004. Performance analysis of a neural network based INS/GPS integration architecture for land vehicle navigation, *CD Proceedings of the 4th International Symposium on Mobile Mapping Technology*, Kunming, China.

Chiang, K.-W. and Nassar S., 2002. "INS/GPS Integration Using Neural Networks for Land Vehicle Navigation Applications," presented at *ION GNSS 15th International Technical Meeting of the Satellite Division*, Portland, OR, 2002.

El-Rabbany, A. and El-Diasty, M., 2004. An efficient neural network model for de-noising of MEMS-based inertial data. *Journal of Navigation* (57): 407-415.

El-Sheimy, N. and Abdel-Hamid, W., 2004. An adaptive neuro-fuzzy model to bridge GPS outages in MEMS-INS/GPS land vehicle navigation, *ION GNSS 17th International Technical Meeting of the Satellite Division*, Long Beach, California, USA.

Farrell, J. and Barth, M., 1999. *The Global Positioning System and Inertial Navigation*. McGraw-Hill, New York, 333 pp.

Goodall, C., El-Sheimy, N. and Chiang, K.-W., 2005. The development of a GPS/MEMS INS integrated system utilizing a hybrid processing architecture, *ION GNSS 18th International Technical Meeting of the Satellite Division*, Long Beach, CA, pp. 1444-1455.

Jwo, D.-J. and Huang, H.-C., 2004. Neural network aided adaptive extended Kalman filtering approach for DGPS positioning. *Journal of Navigation*: 449-463.

Kaygisiz, B.H., Erkmen, I. and Erkmen, A.M., 2004. GPS/INS Enhancement for Land Navigation using Neural Network. *The Journal of Navigation*, 57(2): 297-310.

Korniyenko, O.V., Sharawi, M.S. and Aloi, D.N., 2005. Neural network based approach for tuning Kalman filter, *IEEE Electro/Information Technology Conference (EIT 2005)*, Lincoln - Nebraska, May 22-25,, pp. 1-5.

Semeniuk, L. and Noureldin, A., 2006. Bridging GPS outages using neural network estimates of INS position and velocity errors. *Measurement Science and Technology*, 17(10): 2783-2798.

Titterton, D.H. and Weston, J.L., 2004. *Strapdown Inertial Navigation Technology - 2nd Edition*. The Institution of Electrical Engineers, Stevenage, U.K.

Wang, J.J., Wang, J., Sinclair, D. and Watts, L., 2006a. Designing a Neural Network for GPS/INS/PL Integration, *IGNSS2006*. Menay Pty Ltd, Gold Coast Australia.

Wang, J.J., Wang, J., Sinclair, D. and Watts, L., 2006b. A Neural Network and Kalman Filter Hybrid Approach for GPS/INS Integration. In: G.T. Council (Editor), *IAIN/GNSS 2006.* Korean Institite of Navigation and Port Research, Jeju, Korea, pp. 277-282.