A Neural Network and Kalman Filter Hybrid Approach for GPS/INS Integration

Jianguo Jack Wang[1], Jinling Wang[1], David Sinclair[2], Leo Watts[2]

[1]School of Surveying and Spatial Information Systems, University of New South Wales, Australia
[2]QASCO Surveys Pty. Limited, Australia

Abstract

It is well known that Kalman filtering is an optimal real-time data fusion method for GPS/INS integration. However, it has some limitations in terms of stability, adaptability and observability. A Kalman filter can perform optimally only when its dynamic model is correctly defined and the noise statistics for the measurement and process are completely known. It is found that estimated Kalman filter states could be influenced by several factors, including vehicle dynamic variations, filter tuning results, and environment changes, etc., which are difficult to model. Neural networks can map input-output relationships without apriori knowledge about them; hence a proper designed neural network is capable of learning and extracting these complex relationships with enough training. This paper presents a GPS/INS integrated system that combines Kalman filtering and neural network algorithms to improve navigation solutions during GPS outages. An Extended Kalman filter estimates INS measurement errors, plus position, velocity and attitude errors etc. Kalman filter states, and gives precise navigation solutions while GPS signals are available. At the same time, a multi-layer neural network is trained to map the vehicle dynamics with corresponding Kalman filter states, at the same rate of measurement update. After the output of the neural network meets a similarity threshold, it can be used to correct INS measurements when no GPS measurements are available. Selecting suitable inputs and outputs of the neural network is critical for this hybrid method. Detailed analysis unveils that some Kalman filter states are highly correlated with vehicle dynamic variations. The filter states that heavily impact system navigation solutions are selected as the neural network outputs. The principle of this hybrid method and the neural network design are presented. Field test data are processed to evaluate the performance of the proposed method.

Key words: hybrid, neural network, Kalman filter, navigation solution

1. Introduction

GPS/INS integrated systems have been becoming a popular tool to directly georeference mobile mapping vehicles. INS measures vehicles attitude, velocity and position at a high data rate, with accurate positioning correction provided by DGPS at a relatively low data rate, using Kalman filter (KF) or other real-time data fusion method. The performance of an integrated system depends not only on the quality of each subsystem but also on the data fusion method. As the predictions of a KF diverge without filter measurement update with GPS, the performance of a GPS/INS integrated system degrades rapidly if GPS signals are unavailable. It is a challenging issue to develop optimal real-time data fusion methods for GPS/INS integration that can improve system performance, especially during GPS outages.

KF is the optimal filter for modeled processes, and the core of most INS/GPS integrated systems implemented to date[1]. 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. On the other hand, KF has some shortcomings. The system dynamic models need to be completely known. But in practice few systems can meet such a requirement. Another problem with KF is its drift in prediction mode when GPS signals are lost. 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 error [2]. This is an inherent disadvantage of Kalman filter predictions.

Neural networks (NNs) have been proposed as a multi-sensor integrator [3, 4]. It is well known that NNs are capable of adapting themselves to learn 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, Kalman Filter still remains at the forefront of INS/GPS integration.

Combining KF with NN to circumvent their inherent shortcomings and improve overall performances of INS/GPS integrated systems is a potential solution. A NN aided adaptive extended KF (EKF) was proposed by Jwo and Huang [5]. A NN based approach for tuning KF was developed by Korniyenko et al [6]. NN and KF were combined together to bridge GPS outages [2]. NN model was used for de-noising MEMS-based inertial data [7].

This paper presents a new hybrid method that improves the performance of an INS/GPS integrated system by employing NN to reduce the KF state drift during GPS outages. The KF states and their impact on system navigation solutions during GPS outages are investigated using field test data. The cross correlations between parameters representing vehicle dynamic variation and the KF error states are analyzed. The inputs and outputs of a NN are selected as the parameters representing vehicle dynamic variations and the KF error states that are highly correlated with the variation and have serious impact on the navigation solution. A multi-layer feed-forward back-propagation neural network is trained to map these input-output relationships at the same rate of KF measurement update. The NN is merged into an EKF for GPS/INS integration. The outputs of the trained NN are used to compensate KF state drifts and improve navigation solutions when no GPS measurements are available.

This paper is organized as follows. Section 2 analyzes the role of each KF state in navigation solutions during the filter prediction, and canvasses cross-correlation between parameters representing the vehicle dynamic variation and the filter error states. The inputs and outputs of a NN are defined in Section 3. Pre-processing is needed for NN outputs to establish better input-output relationships. Section 4 describes the design of the NN, and the combination of NN and EKF. Section 5 presents and discusses testing results, and the concluding remarks are given in Section 6.

2. Analysis of KF States

2.1 The role of KF states

A tightly coupled EKF is applied for GPS/INS integration, which makes it possible to update the filter even with less than four GPS signals, and can provide better accuracy and is less sensitive to satellite dropouts than a loosely coupled one. The error states (instead of whole-value filter states) are chosen for the EKF. The complexity of the INS error model depends on the model for INS sensor measurement errors, as well as the gravity uncertainty [8].The EKF includes the following 24 states:

$$\begin{aligned}
\mathbf{x}_{Nav} &= [\,\delta r_N, \delta r_E, \delta r_D, \delta v_N, \delta v_E, \delta v_D, \delta\psi_H, \delta\psi_P, \delta\psi_R\,]^T \\
\mathbf{x}_{INS} &= [\nabla_{bx}, \nabla_{by}, \nabla_{bz}, \nabla_{fx}, \nabla_{fy}, \nabla_{fz}, \varepsilon_{bx}, \varepsilon_{by}, \varepsilon_{bz}\,]^T \\
\mathbf{x}_{Ant} &= [\,\eta_x, \eta_y, \eta_z\,]^T \\
\mathbf{x}_{Grav} &= [\delta g_N, \delta g_E, \delta g_D]^T
\end{aligned} \tag{1}$$

where $\mathbf{x}_{Nav}$, $\mathbf{x}_{IMU}$, $\mathbf{x}_{Ant}$ and $\mathbf{x}_{Grav}$ are the navigation error vector, the INU sensor measurement error vector, the GPS antenna to INS lever arm measurement error vector and gravity uncertainty, respectively. Subscript *b* stands for bias and subscript *f* stands for scaling factor.

It is important to develop proper dynamic and stochastic models for the system errors as this is the key to understanding their effects on the navigation solution, and to estimate these errors using external measurements. The following complete terrestrial INS psi-angle error model is adopted in the system.

$$\begin{aligned}
\delta\dot{\mathbf{v}} &= -(\omega_{ie} + \omega_{in}) \times \delta\mathbf{v} - \delta\psi \times \mathbf{f} + \delta\mathbf{g} + \nabla \\
\delta\dot{r} &= -\omega_{en} \times \delta\mathbf{r} + \delta\mathbf{v} \\
\delta\dot{\psi} &= -\omega_{in} \times \delta\psi + \varepsilon
\end{aligned} \tag{2}$$

where $\delta\boldsymbol{v}$, $\delta\boldsymbol{r}$, and $\delta\psi$ are the velocity, position, and attitude error vectors respectively; ∇ is the accelerometer error vector; $\delta\boldsymbol{g}$ is the error in the computed gravity vector; and $\boldsymbol{\varepsilon}$ is the gyro drift vector.

The strap-down INS navigation computation diagram is expressed in Figure 1. The item ΔV_{ib}^{b} is delta velocity from accelerometers, $\Delta\theta_{ib}^{b}$ is the angular rates and C_n^b the direction cosine matrix from b-frame to n-frame.

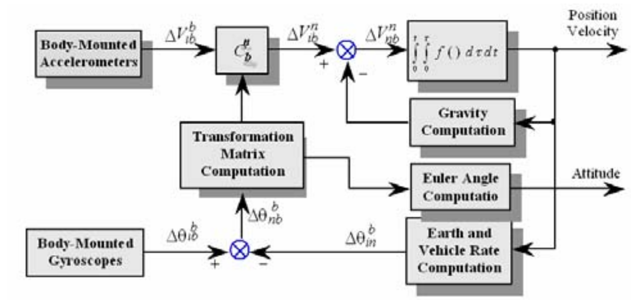

Figure 1. Strap-down INS navigation computation diagram

The impact of each EKF state on the system navigation solutions is different. Table 1 presents the navigation errors with different combination of the EKF states to be updated, using the field test data with 60 seconds GPS outage.

Table 1. The impacts of the KF states

EFK states								Navigation error		
abias	asf	gbias	ant	grav	pos	vel	atti	Pos (m)	Vel (m/s)	Atti (sec)
v	v	v	v	v	v	v	v	0.0	0.0	0.0
x	x	x	x	x	x	x	x	14.5	0.29	69
x	x	x	x	x	x	x	v	2.6	0.08	18
x	x	x	x	x	x	v	x	12.1	0.26	69
x	x	x	x	x	x	v	v	1.05	0.03	18
x	x	x	x	x	v	v	v	1.0	0.03	18

The ‘x’ in the table indicates that an EKF state is not updated whilst the ‘v’ indicates that the associated state is updated. The navigation error is quite large without any EKF state updated after 60 seconds, while it drops much with only the navigation error states (position, velocity and attitude) updated. The attitude error states play the most important role in reducing the navigation errors. Therefore, it is possible to reduce the EKF predicted navigation errors without GPS updates by estimating the attitude and velocity states errors according to some factors, such as vehicle dynamic variation and environment (temperature) change etc.

2.2 Cross Correlations

If the process noise and the measurement noise are white and Gaussian, the initial state is Gaussian, and the system is linear, the EKF in a GPS/INS integrated system is convergent and the states of the EKF keep stable after adequate maneuvers[1]. However, the actual EKF states vary with time because these assumptions are not always valid. The factors causing the filter state variation include INS sensor imperfection, gravity variation and inaccurate EKF modelling etc.

Figure 2 is an example of an EKF state’s variation with time, which is largely caused by the vehicle dynamic variations. The top curve in the figure is the vehicle heading change rate, and the bottom one is the corresponding EKF orientation error state. There are some relationships between them, which is unable to be modeled, but could be mapped by a properly designed NN after adequate training.

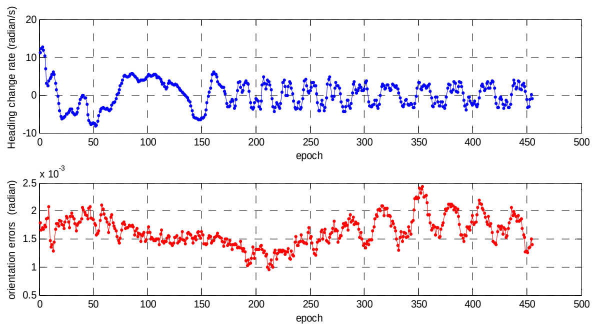

Figure 2. EKF states variation with time

The challenging issue is to find a proper method to predict the state variation. The vehicle heading change-rate is selected to analyze the impact of the vehicle dynamic variation on the filter state variations. Table 2 presents the maximum values of cross correlation function between the heading changing rate and the EKF states using field test data.

Table 2. Cross correlation function between the heading changing rate and some EKF states

KF state	δv_N	δv_N	δv_D	∇_{bx}	∇_{by}	$\delta\psi_H$	$\delta\psi_P$	$\delta\psi_R$
Crosscorr	0.6	0.45	0.45	0.5	0.7	0.45	0.45	0.4

The δv_N , δv_N and δv_D in the table are the EKF velocity error states in three directions. ∇_{bx} and ∇_{by} are the horizontal accelerometer biases, and $\delta\psi_H$, $\delta\psi_P$ and $\delta\psi_R$ are the attitude error states in three directions. The results in the table indicate that some EKF states have relative high cross correlation with the vehicle dynamic variation, represented by the heading changing rate. So it is possible to find the relationships between them.

3. NN Inputs and Outputs

3.1 NN Inputs Selection

The principal strategy of the proposed NN and EKF hybrid method is using NN to map the relationships between vehicle dynamic variations during EKF measurement updates and the EKF calculated error states after each update. The NN training procedure is executed at the GPS sampling rate. Then the well-trained NN can be used to improve the EKF prediction at preferred system output rate (up to the IMU sampling rate) during the GPS outages. 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. For land vehicle applications, vertical movement is limited, and the NN input parameters can be selected as follows:

$$NN_{in} = [\Delta v_N, \Delta v_E, \Delta\psi_H, \psi_H] \qquad (3)$$

It should be noticed that both the heading angle and its change rate are selected as inputs. As the heading angler ψ_H (green curve in Figure 3) is limited to the change between π and $-\pi$, its changing rate $\Delta\psi_H$ has spikes when the heading angle has jumps, as the red curve shown in the figure. These jumps will disturb the NN training, and need to be removed. The blue curve in the figure is $\Delta\psi_H$ after the spikes are removed. These jumps may also happen to the pitch and roll parameters for airborne applications.

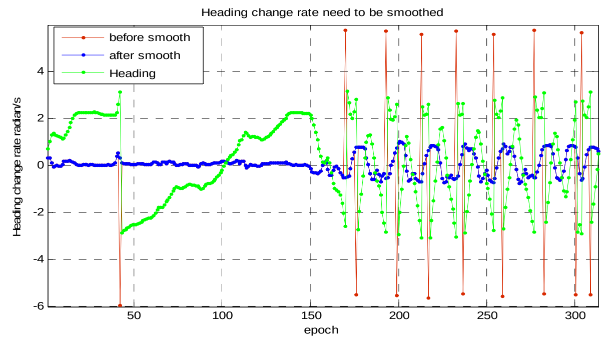

Figure 3. Smooth heading change rate.

3.2 NN Outputs Selection

The NN outputs, or the training targets, are selected as the EKF error states that largely impact the system navigation solution, and have high cross correlations with parameters representing a vehicle's dynamic variation. According to the analysis results in Section 2, the NN inputs are the filter states of velocity and orientation errors, as follows:

$$NN_{out} = [\delta v_N, \delta v_E, \delta v_D, \delta\psi_H, \delta\psi_P, \delta\psi_R] \qquad (4)$$

The system navigation error can be effectively attenuated if above filter states variation can be predicted. As shown in Figure 4, the EKF states variations have two frequency domains. The low frequency domain is potentially caused by temperature change, gravity variation and EKF modelling errors etc., which can be estimated by linear polynomial curve fitting. The high frequency domain is largely caused by vehicle maneuver and INS sensors imperfection etc., which will be mapped with NN.

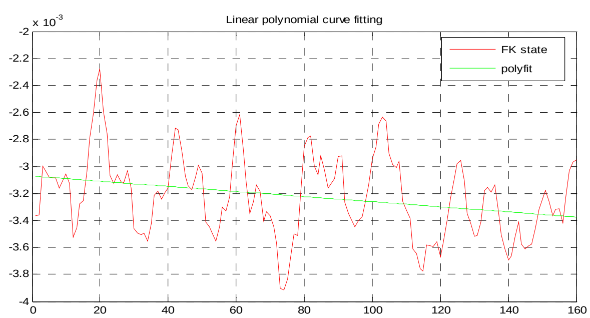

Figure 4. NN input and output sample

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

4.1 NN Supervised Learning

NN can be designed to perform complex functions and solve problems that are difficult for conventional computers or human beings. 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 6. 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.

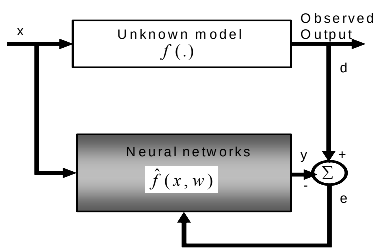

Figure 5. NN learning procedure[4]

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.

4.2 Multi-layer Feed-forward Neural Network

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 shown in Figure 6. The number of the layers is appended as a superscript to the variable of interest, to distinguish them between each of these layers.

The layers of a multi-layer network play different roles. A layer that produces the network output is called an output layer. All other layers are hidden layers. A three-layer network shown in Figure 6 has one output layer (layer 3) and two hidden layers (layer 1 and 2). 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.

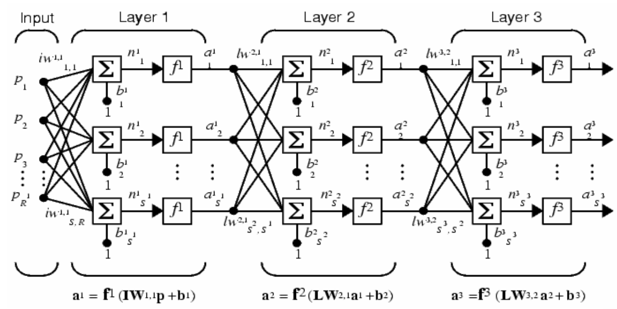

Figure 6. Three layer neural network [9]

The transfer function ***f*** of each layer can be selected individually. The network output is the function of the network input with all the function of each layer imbed together, as expressed by equation (5).

$$a^3 = f^3(LW^{3,2} f^2(LW^{2,1} f^1(IW^{1,1}p + b^1) + b^2) + b^3 = y \tag{5}$$

Multiple-layer networks are quite powerful. For instance, a network of two layers, where the first layer is sigmoid and the second layer is linear, can be trained to approximate any function (with a finite number of discontinuities) arbitrarily well. More details about neuron model and the architecture of NN and can be found in the Matlab Neural Network Toolbox [9]. 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. They have 12, 18 and 6 neurons, respectively, for 100 epochs' training set.

4.3 Hybrid System Architecture

The EKF and NN hybrid system block diagram is presented in Figure 7. As long as the DGPD signal is available, the system is in the training phase. The learning process is continuously adjusting its parameters at KF measurement update. During GPS outages, the NN parameters are used in the prediction phase to estimate the corresponding KF states.

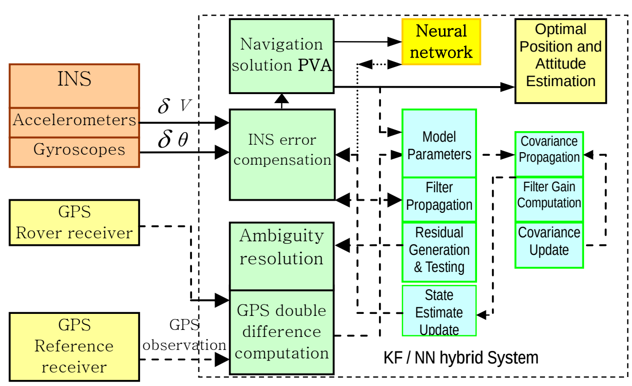

Figure 7. Hybrid system flow chart

The vehicle dynamic variation derived from the navigation solution is continuously as the input of the NN. During the training phase, the EKF produces navigation solutions, and updates the filter states with the GPS measurements, as the detached lines in Figure 7 expressed. Some of the updated filter states are selected as the target for the network training, adjusting parameters in the network to match the NN output with the target. If the GPS signal is unavailable and the network is well trained, its output is used for INS error compensation.

5. Results and Discussions

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. Another MEMS INS (Crossbow's IMU 400CC-100) was also tested together. 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 8.

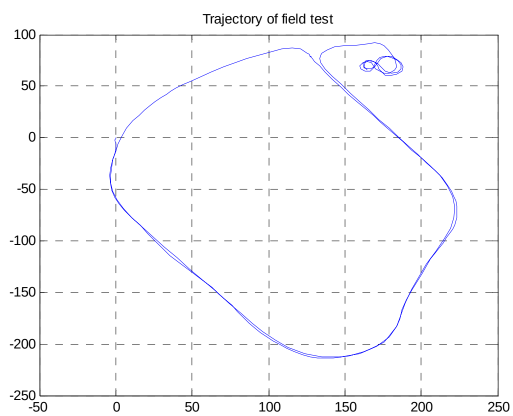

Figure 8. Horizontal trajectory of the field test

The data were processed with a modified AIMS™ software with the proposed Neural Network algorithm to evaluate the proposed EKF and NN hybrid approach for GPS/INS integration. The AIMS™ software was developed by the Center for Mapping at the Ohio State University (OSU) for direct geo-referencing large scale mapping and precise positioning applications [10]. The row measurement data were processed by AIMS™ first to generate reference navigation solutions and EKF error states. These data were then processed with the proposed hybrid algorithm.

5.1 NN Training Results

The NN was trained with an incremental batch method. A set of 100 epochs input vectors were applied to train the NN by adjusting the 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 different learning rules. Conjugate gradient learning algorithm was used as it can reduce oscillatory behavior in the minimum search and reinforces the weight adjustment with previous successful path direction[11].

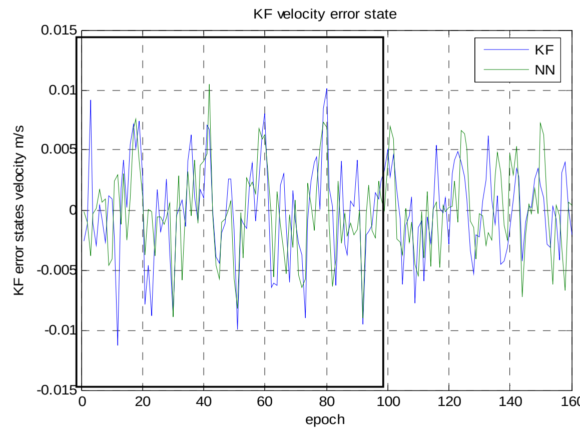

Figure 9a. NN training results with Boeing's INS

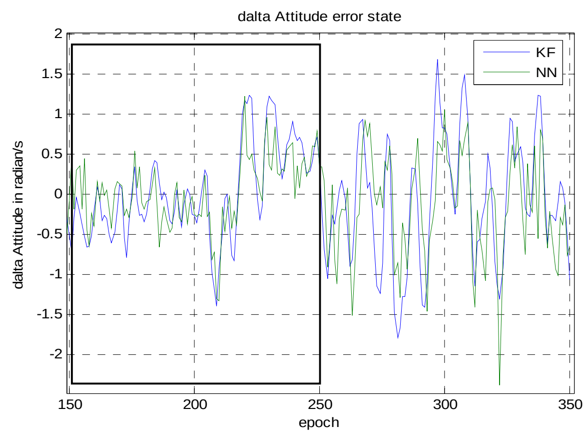

Figure 9b. NN training results with Crossbow's INS

The training results of two parameters with two different INS are shown in Figures 9a and 9b. 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 less similar to the target in comparison with the output in the training window. This means that NN after training can make reasonable prediction for quite a long period. This is useful to improve system navigation solutions during GPS signal outages. It is noticed that different training set requires different number of neurons to achieve optimal training results.

5.2 Hybrid Navigation Results

The field test data with trajectory in Figure 8 was processed. In order to access the performance of the hybrid method, GPS outages were simulated along various portions of test trajectory. The NN was trained 100 seconds before each GPS outage, which lasts for 60 seconds. During the GPS outages, the KF states selected as the output of the NN, which changes with the NN inputs (the vehicle dynamic variation), were applied for the INS measurement correction. 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 data from both Boeing's C-MIGITS II and Crossbow's IMU 400CC-100 were processed. The results are listed in the Table 3a and 3b.

Table 3a. Test results with Boeing's INS

section	δx (m)		δv (m/s)		$\delta\psi$ (sec)	
1	4.5	6.8	0.16	0.23	23	33
2	3.1	5.2	0.18	0.21	25	31
3	3.4	5.3	0.16	0.22	32	41
4	2.9	6.1	0.13	0.24	31	59
5	5.3	9.7	0.22	0.36	42	81
improvement	42%		32%		37%	

Table 3b. Test results with Crossbow's INS

section	δx (m)		δv (m/s)		$\delta\psi$ (sec)	
1	632	725	29	33	94	188
2	732	868	27	30	36	58
3	213	530	11	20	37	78
4	209	269	9.9	14	19	69
5	232	307	10	18	11	49
improvement	25%		24%		55%	

The test results above show that the NN and KF hybrid method can improve the navigation solutions, in all terms of position, velocity and attitude, during the GPS outages. The NN after training works well around the training window. Its output can make reasonable predictions after the training window, and is useful to correct the EKF predictions. Further investigation is needed to develop a more effective NN algorithm to improve E KF estimates during longer GPS outages. The same NN architecture works well for different types of INS. 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 and outputs of a NN are selected as the parameters representing a vehicle's dynamic variation and the KF error states that have serious impact on the navigation solution. The NN is merged into an EKF for GPS/INS integration. The outputs of the trained NN are used to compensate KF 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 filter predicted error states (NN output). Primary test results have shown that a three-layer feed-forward NN 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 40%, 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/Pseudolite/INS to Geo-reference Airborne Surveying and Mapping Sensors.

Reference

[1] J. Farrell and M. Barth, *The Global Positioning System and Inertial Navigation*. New York: McGraw-Hill, 1999.

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

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

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

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

[6] O. V. Korniyenko, M. S. Sharawi, and D. N. Aloi, "Neural network based approach for tuning Kalman filter," presented at IEEE Electro/Information Technology Conference (EIT 2005), Lincoln - Nebraska, May 22-25,, 2005.

[7] A. El-Rabbany and M. El-Diasty, "An efficient neural network model for de-noising of MEMS-based inertial data," *Journal of Navigation*, pp. 407-415, 2004.

[8] R. Da, G. Dedes, and K. Shubert, "Design and Analysis of a High-Accuracy Airborne GPS/INS System," presented at GPS/GNSS, Kansas City, Missouri, 1996.

[9] H. Demuth and M. Beale, "Neural Network Toolbox," 4.0 ed: The MathWorks, Inc., 2004.

[10] D. A. G.-. Brzezinska and C. K. Toth, "AIMS? An Alternative Tool for Coastal Mapping, Marine Geodesy," I*nternational Journal for Marine Geodesy,* vol. 22, pp. 129-137, 1999.

[11] K.-W. Chiang and S. Nassar, "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.