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Neural Network Aided Kalman Filtering For Integrated GPS/INS Navigation System

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Abstract

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, KF can optimally estimate a system's states. Without measurement updates, Kalman filter's prediction diverges; therefore the performance of an integrated GPS/INS navigation system may degrade rapidly when GPS signals are unavailable. This paper presents a neural network (NN) aided Kalman filtering method to improve navigation solutions of integrated GPS/INS navigation system. In the proposed loosely coupled GPS/INS navigation system, 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, 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.

Keywords*: Neural network, GPS/INS, Kalman filter, vehicle navigation*

1. Introduction

Outdoor vehicle navigation is always a challenge to consider requirements for accuracy and reliability operation environment. It is well known that GPS measurements are regularly obstructed in urban environments. Positioning accuracy in such environments is significantly degraded, it is not possible to obtain a GPS position fix at all [1]. With the development of GPS and INS technologies in recent decades, it is an increasing trend to use integrated GPS and INS systems for vehicle navigation. GPS is capable of providing accurate position and velocity information, if four GPS satellites with good geometry at least 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 un-usable. 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 INS, its inertial sensors are subjected to the full range of heading and attitude changes and turn rates, the vehicle experiences along its path. Therefore, GPS and INS are often integrated together to overcome the drawbacks associated with each system.

GPS and INS are usually integrated with 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 modeled processes, and the core of most GPS/INS integrated systems implemented to date [2]. It can optimally estimate the position, velocity and attitude of a moving vehicle using

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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. 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 GPS/INS integration system using KF data fusion.

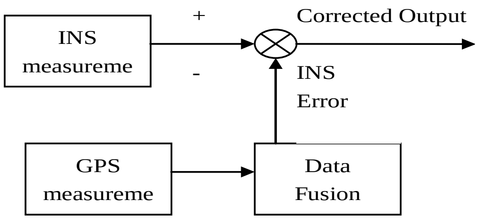

Figure 1. GPS/INS integration using data fusion

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 [3]. 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 [4], [5], [6]. NNs have been proposed as a multi-sensor integrator [7], [8]. It is well known that NNs are capable of mapping input-output relationships [9]. 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. 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/INS integration. Due to the deficient observation and model uncertainty, an adaptive factor based on neural network is constructed using innovation, thus GPS/INS adaptively integrated navigational algorithm based on neural network is designed. Test data is used to validate the proposed algorithm. The simulation results show that if the neural network is used as adaptive state estimator, the error of state estimation is reduced considerably and the computing simple, robust and high accuracy characteristic are obtained.

2. 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. Given an unknown model or an unknown functional relationship with its input and observed target. A neural network learns to fit the relationship by comparing the output from a neural network with the observed target. It then adjusts the value of its weight until the error meet a predefined accuracy; or after certain times iteration.

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. 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.

The NN is trained with an incremental batch method. A set of 5000 epochs input vectors were applied to train the 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 [10]. 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 2.

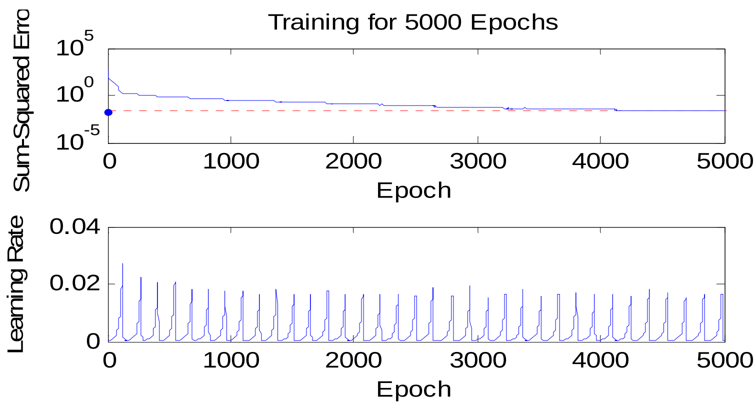

Figure 2. The curve of training error and learning rate during NN training phase

3. Neural Network Aided Kalman Filtering

Combining KF with NN to outwit their inherent shortcomings and improve the overall performances of GPS/INS integrated systems is a potential solution. A NN aided adaptive EKF was proposed by Jwo and Huang [11]. A NN based approach for tuning KF was developed by El-Rabbany etal [12]. NN and KF were combined together to bridge GPS outages. NN model was used for de-noising MEMS-based inertial data. NN is also employed to map the platform dynamic with corresponding Kalman filter states to smooth system outputs and to bridge GPS outages [13]. A new EKF and NN hybrid method is introduced in this paper to improve the performance of integrated GPS/INS 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 parameters used to correct EKF gain.

The block diagram of proposed EKF and NN hybrid system is presented in Figure 3. As long as the GPS signal is available; the system operates in the training phase.

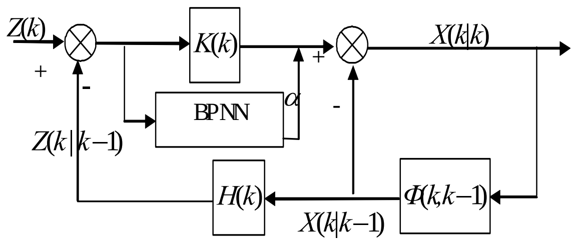

Figure 3. The block diagram of proposed EKF and NN hybrid system

During GPS outages, no GPS signal is available. The NN output is used 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. In Integrated Navigation System, as the number of measurement is less than the number of state parameters, and the neural network has a good feature of non-linear approximate, adaptive and fault-tolerant, it can be used to construct the adaptive factor α_{k}.

$$\alpha_{\mathrm{k}} = \begin{cases} 1 & \left|\Delta \tilde{X}_k\right| \le c \\ \dfrac{c}{\left|\Delta \tilde{X}_k\right|} & \left|\Delta \tilde{X}_k\right| > c \end{cases}$$

The adaptive factor based on neural network, can greatly reduce the computation time and meet the demand for real-time navigation. The curves of α_{k} theoretical value is shown as figure 4.

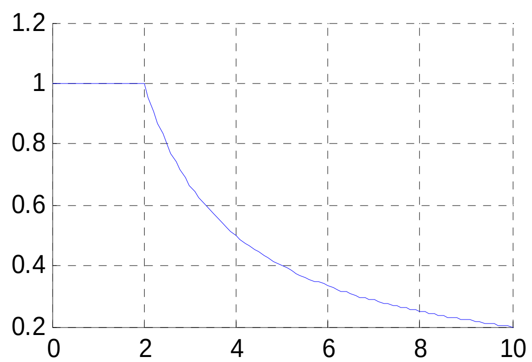

Figure 4. The curves of α_{k} the oretical value

The algorithm of EKF based on NN is given as follow:

$$P(k\,|\,\mathrm{k}-1) = \Phi(k,k-1)P(k-1|k-1)\Phi^{\mathrm{T}}(k,k-1) + Q(k)$$
$$\hat{X}(k|k\text{-}1) = \Phi(k,k\text{-}1)\hat{X}(k\text{-}1|k\text{-}1)$$
$$\varepsilon(k) = \alpha\left[Z(k) - H(k)\hat{X}(k|k-1)\right]$$
$$K(k) = P(k|k-1)H^{T}(k)[H(k)P(k|k-1)H^{T}(k) + R(k\text{-}1)]^{-1}$$
$$\hat{X}(k|k) = \hat{X}(k|k-1) + K(k)\varepsilon(k)$$
$$P(k|k) = [I\text{-}K(k)H(k)]P(k|k\text{-}1)[I\text{-}K(k)H(k)]^{T} + K(k)R(k\text{-}1)K^{T}(k)$$

Based on the algorithm, we can test the location accuracy of the vehicle when the signal of GPS is outrage.

4. Test Results

Field test data were collected to evaluate the proposed hybrid method. 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. It is well known that if the process can be approximated with a linear model plus white noise with known statistics, then an optimal (minimum mean squared error) Kalman Gain can be evaluated. In this application, we consider a constant velocity model. A full implementation for, and estimation will require 12 states to account for the coloured noise. The results presented in this work correspond to the estimation of information. 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 5000 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 error curve of velocity is shown as figure 5:

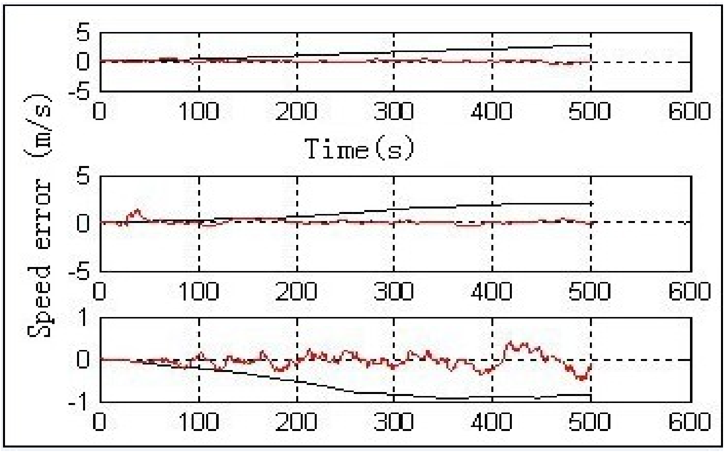

Figure 5. The error curve of velocity

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.

5. Conclusion

This paper has presented a NN and KF hybrid method to reducing KF drift during GPS outages. Based on the previous results and analysis presented earlier, in this section, some remarks and conclusions are in place. The proposed method, for preserving the KF update functionality, has effectively reduced position and velocity drifts during the type of GPS outages simulated. Without using the proposed method, the long-term MEMS-INS standalone navigation accuracy of a traditional EKF is unacceptable for many navigation applications, particularly land-vehicle navigation applications. This research has two main objectives; First, to improve the performance of inertial sensors to facilitate GPS integration for land vehicle navigation applications; Second, to overcome the limitations and poor prediction of the conventional EKF solution of INS/GPS integration particularly during GPS signal or solution outage. The experimental validation results have shown the efficiency and significant effect of the proposed techniques in reducing position and velocity drifts during GPS outages under the scenarios tested. The inputs of the NN are selected as the measurements of the EKF in a loosely coupled GPS/INS 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 GPS/INS 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.

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