ENHANCING INS/GPS INTEGRATION UTILIZING DYNAMIC NEURAL NETWORK MODEL FOR MOBILE MAPPING APPLICATIONS

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ABSTRACT:

Efficient inventory and analysis of highway and road network features requires a reliable and accurate mobile mapping system (MMS). Advances in Geomatics technologies such as the Global Positioning System (GPS), Inertial Navigation Systems (INS), and laser/ultrasonic imaging sensors made it possible to offer such system. The ultimate objective of this research is to suggest a new INS/GPS integration technique that improves the positioning accuracy of the overall system, especially during relatively long GPS outages, which could be experienced by a MMS in urban canyons. If left unaided, INS position errors grow to large values due to the mathematical integration of sensor errors performed during the INS mechanization procedure. In case of long GPS outages, the MMS may suffer from an increasingly position and attitude errors over time. It was also reported that Kalman filtering may not provide reliable estimates of the INS position errors during relatively long GPS outages, especially when tactical and low cost INS is utilized for the MMS. Several artificial intelligence techniques were proposed as replacement for Kalman filtering. However, none of these methods considered the time dependence nature of the INS error, which may also lead to inadequate performance during long GPS outages. Thus, a model capable of establishing time-dependent relationship of the INS errors during long GPS outages is necessary. This research proposes a dynamic neural network model for the INS position and velocity errors utilizing Input Delayed Neural Networks (IDNN). Such network architecture depends not only on the current input to the network but also on few previous inputs and outputs. While the navigation system is relying on INS during GPS outages, IDNN model mimics the patterns of the INS errors and provide reliable prediction of the INS position and velocity errors. The proposed IDNN model is evaluated using real field test INS and GPS data collected during real road tests. The results showed that the IDNN model provided at least 25% enhancements in the positioning accuracy if compared to Kalman filtering and other artificial intelligence models.

1. INTRODUCTION

1.1 Mobile Mapping

With advances in Geomatics technologies such as the Global Positioning System (GPS), Inertial Navigation Systems (INS), and laser/ultrasonic imaging sensors, a considerable portion of such information can be collected from a moving platform [1]. Systems that integrate the above technologies are called Mobile Mapping Systems (MMS). The advantage of the MMS-mode of operation is that data collection can be performed significantly faster when compared to traditional survey techniques. Consequently, mobile mapping systems are more economic. Implementation of automatic data integration techniques also provides substantial improvements in efficiency over traditional survey methods. In general, the complete MMS consists of three major components – a Mobile Mapping Van (MMV), a Georeferencing Module (GM), and a Photogrammetric and GIS Module (PGM) [2]. The accuracy of georeferencing relies mostly on the accuracy of INS/GPS data fusion module and how reliable the system can provide accurate positioning solution during GPS outages, which are usually experienced in urban canyons.

1.2 INS/GPS

There are several situations where GPS experience total system outage (due to satellite signal blockage) or deterioration of accuracy (due to multipath effects and clock bias error) [3].

Therefore, GPS is always combined with inertial navigation system (INS), which is a self-contained system incorporating three orthogonal accelerometers and three orthogonal gyroscopes monitoring the vehicle's linear accelerations and rotation rates. However, the INS accuracy deteriorates with time due to the inherent sensor errors (white noise, correlated random noise, bias instability, and angle random walk) that exhibit considerable long-term growth [4].

The integration of GPS and INS, therefore, provides a navigation system that has superior performance in comparison with either a GPS or an INS stand-alone system. Kalman filtering (KF) was applied for number of years to provide an optimal INS/GPS integrated module [5]. More recently, several techniques based on artificial intelligence (AI) have been proposed to replace KF in order to eliminate some of its inadequacies [6]. All of the existing AI – based models relates the INS error at certain time instant to the INS position or velocity at the same instant. The major drawback of such models is their lack of mimicking the INS error trend at either the INS position or velocity during the update procedure. Therefore, in case of relatively long GPS outages, any of the existing AI–based models may not be capable of providing reliable and accurate positioning solution, especially for tactical and low cost systems [7].

1.3 Objectives

In this research, we aim at developing an AI–based INS/GPS integration module to increase the accuracy and the robustness of MMS. Such AI-based module will be taking into consideration the INS error trend and thus providing better positioning accuracy for long GPS outages. Input delay neural network (IDNN) is proposed for this purpose as a dynamic neural network mimicking the INS error trend and models both the INS position and velocity errors based on the current and some past samples of INS position and velocity, respectively. This way more accurate positioning

2. DYNAMIC NEURAL NETWORK

Dynamic networks are generally more powerful than static networks (although somewhat more difficult to train). Because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns [8]. In fact, to predict temporal patterns, an ANN requires two distinct components: a memory and an associator. The memory holds the relevant past information, and the associator uses the memory to predict future events. In this case the associator is simply a static neural network, and the memory is generated by a time delay unit (or shift register) that constitutes the tapped delay line [8]. In fact, the static netowrk model does not perform temporal processing since the vector space input encoding gives the model no information about the temporal relationship of the inputs. In fact, INS velocity or position error prediction is a procedure where previous states of the INS velocity and position errors have to be seriously considered.

2.1 IDNN – Input Delay Neural Network

The use of an internal time delay operator within the static network leads to the time delay neural network, also referred to as the Input-Delay Neural Network (IDNN). In this case, the static network is transformed into a dynamic network since the number of the embedded time delays provides the network with a short-term memory [8,9]. The number of neurons associated with the input layer is equal to the input variables; therefore, the IDNN integrates temporal context information implicitly and thus recognize temporal patterns that have arbitrary time intervals or arbitrary lengths of temporal effects. Thus the IDNN becomes suitable for situations where temporal pattern should be considered and is affecting the prediction accuracy, which is the major objective of this study. Figure 1 shows a single neuron with a tapped delay line that corresponds to a buffer containing the p most recent inputs generated by a delay unit operator D. It should be also noted that $w_i(k)$ are the synaptic weights for neuron i, and b_i is its bias while $G(.)$ is a sigmoid activation function associated with neuron i.

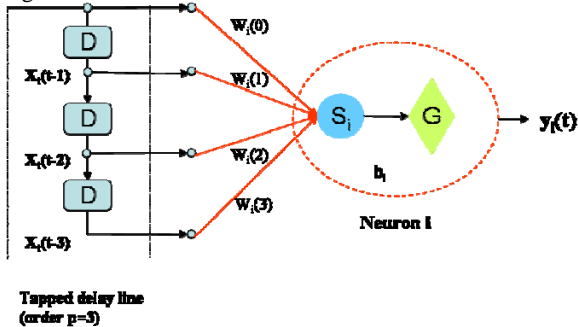Tapped delay line
(order p=3)

Figure. 1. Single Neuron with Input Delay Line

During the update procedure, we use a second-order back-propagation variation namely the Levenberg-Marquardt back-propagation (LMBP) [9]. The network training process is performed by providing input-output data to the network, which targets minimizing the error function by optimizing the network weights. LMBP uses the second derivative of the error matrix (E) to update the weights of the network in a recursive fashion.

3. METHODOLOGY

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

3.1 Model Architecture

To provide complete navigation solution for the MMV, each of the three directions involves two IDNN modules; the first for the INS velocity error and the second for the residual INS position error. Along each direction, the IDNN velocity module processes the INS velocity at the input while providing the corresponding INS velocity error at the output. After correcting the velocity error and obtaining the position error, the modified INS position is the input to the IDNN position module, which provides the corresponding INS position error at the output. The IDNN modules are updated during the training procedure using both GPS position and velocity updates.

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

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

4. ROAD TEST EXPERIMENTS

The performance of the suggested IDNN-based INS/GPS integration module was examined with a field tests involving the CIMU navigation grade INS and a NovATel OEM-4 GPS receiver. Over the whole trajectory (shown in Figure 2), no natural GPS outages were detected, and thus the position and velocity information obtained from this system in the differential mode will be used as reference when evaluating the overall accuracy. The performance of the IDNN module is examined during artificial *100 sec* GPS outages intentionally introduced to the trajectory in order to test its ability to accurately predict the INS errors and provide reliable position and velocity information. Four artificial GPS outages were selected at different locations of different vehicle dynamics so that the system stability and robustness can be examined.

The IDNN modules were initialized and continued to update while the GPS signal is available. The real-time implementation considered 40 sec window size during the update procedure, which is performed to minimize the error between the IDNN output and the desired response such that RMSE of *0.0001 m* is achieved. However, given the real-time implementation constraint of processing time, the IDNN update procedure for each window was terminated after 100 training epochs apart from the RMSE achieved.
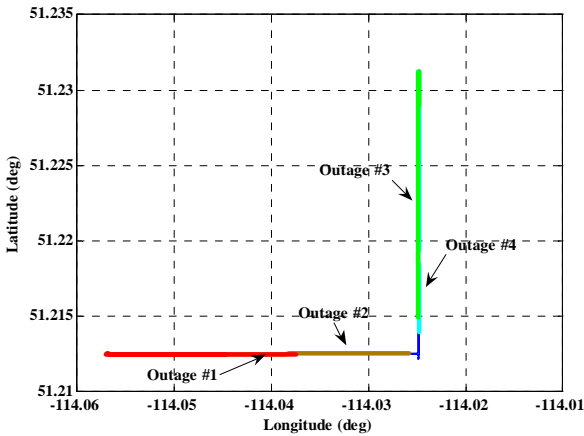

Fig. 2. Test trajectory showing the locations of GPS outages.

In order to examine the value of the proposed IDNN-based module for INS/GPS integration, it is essential to compare the positioning accuracy of the IDNN model to the conventional techniques, predominantly based on KF, which is considered as the base line accuracy level for vehicle positioning in MMS. The KF results were obtained using AINS™, a program developed and provided by the Mobile Multi-Sensor Systems Research Group at the University of Calgary, Calgary, Canada. This program processes the INS and GPS data using a 15 state KF, where the states include three position errors, three velocity errors, three attitude errors, three gyroscope bias errors and three accelerometer bias errors.

5. RESULTS AND DISCUSSION

To investigate the effect of time dependence of the INS error (the output of the IDNN module) on the present and past INS inputs (the input to the IDNN module), we examined the performance of the IDNN position modules during the 4 GPS outages. In this analysis, we compare the performance of the

IDNN module using one time input delay element to the case of two input delay elements and the conventional case of non-input delay elements. As can be depicted from Figure 3 for the North direction and Figure 4 for the East direction, the worst positioning accuracy for all GPS outages was observed for the case of non-input delay network architecture. Accuracy enhancements between 20% and 50% occurred when utilizing one or two-time step input delay architecture. On the other hand, the results clearly show that utilizing two input delay elements has minor improvements to the model performances if compared to the one input delay IDNN architecture. While the proposed IDNN-based module showed slight accuracy improvement when using two input delay elements instead of one, the additional delay element significantly complicated the update procedure and required long training time, which is not desirable for real-time applications.
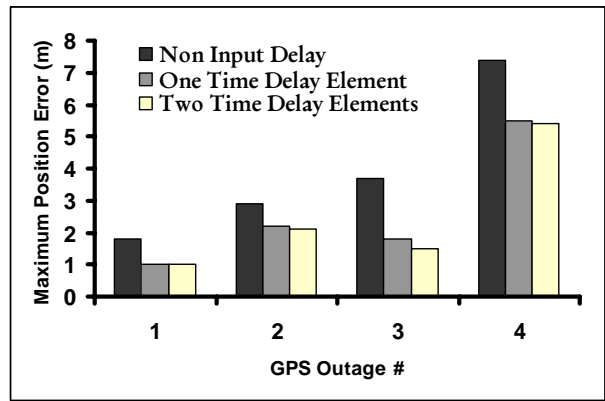

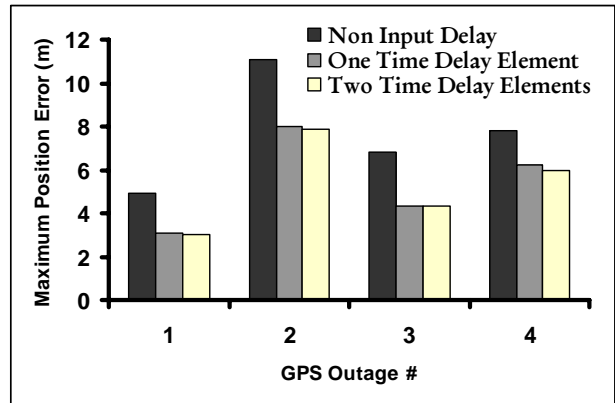**Fig. 3. The position error along the North direction**.

Fig. 4. The position error along the East direction.

By examining the above figures, it can be determined that the IDNN provides consistent level of accuracy for both position components for all GPS outages except for the East position component during the second GPS outage (8m error as noticed in Figure 4). In this particular GPS outage, the vehicle was subject to noticeable change along the longitude and the East velocity component during the whole outage, the update procedure (just prior to this outage) was for a training pattern corresponding to no longitude changes.

In comparison to KF (for the same trajectory and the same *100 sec* GPS outages) the IDNN module was able to reduce the average position error (over the 4 GPS outages) from *8.6m* to *5.9m* for along the East direction and from *7.1m* to *2.7m* for the North direction.

6. CONCLUSION

Motivated by improving positioning accuracy for MMV, this research introduced a new technique for INS/GPS integration based on IDNN. The IDNN module relies on input delay elements at the input layer so that the output INS position or velocity error is modeled based on the present and past samples of the corresponding INS position or velocity. The impact of different delay elements at the input layer on the overall positioning accuracy was investigated. In comparison to conventional KF techniques, the IDNN module showed superior performance for long GPS outages.

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