17th ICEE 2009
Iranian Conference on Electrical Engineering
www.icee.ir/2009

Online Calibration of Inertial Sensors Using Kalman Filters and Artificial Neural Networks

Mohammad Gorji Sefidmazgi[1], Mohammad Farrokhi[1,2]
[1]Department of Electrical Engineering
[2]Center of Excellence for Power System Automation and Operation
Iran University of Science and Technology, Tehran 16846, Iran
mgorjis@gmail.com, farrokhi@iust.ac.ir

Abstract: *Navigation is defined as finding the position of a moving vehicle and inertial navigation is among these methods. Unfortunately, inertial navigation has errors due to different reasons such as inertial sensors. These errors must be corrected by some means. In this paper, a method based on Kalman filters and artificial neural networks is introduced to calibrate inertial sensors during the navigation. Moreover, the proposed method provides better accuracy of the sensor models, when the navigation aid is not present for some times. Simulation results show the effectiveness of the proposed method as compared to the Kalman filter.*

Keywords: Inertial Navigation, Sensor Calibration, Kalman Filter, Artificial Neural Networks.

1. Introduction

Inertial Navigation System (INS) is one of positioning methods that is based on Newton laws of motion. INS is used in different moving vehicles such as airplanes, missiles, ships, and mobile robots. Inertial sensors are part of INS and provide input information to the computing system. Two forms of sensors are used in INS: Accelerometers and Gyroscopes. These sensors provide information to calculate the position, the velocity, and the orientation (or the attitude) of a vehicle along three coordinate axes.

Using gyroscope outputs, the Direction Cosine Matrix (DCM), which converts the body frame (i.e. the roll-pitch-yaw frame) to the navigation reference frame, is updated. By multiplying this matrix to accelerometers outputs, the vehicle acceleration is converted from the body frame to the reference frame. By adding the local gravitational acceleration, the vehicle acceleration in the reference frame is calculated. Finally, double integration of this acceleration provides vehicle movements in the reference frame.

The attitude of a vehicle is defined as the tilt angles between the vehicle and the local horizontal plane (the roll and pitch angles) and the angle between the vehicle and the local geographical north (the azimuth angle). Before navigation, the reference frame must be selected. The reference frame used here for the INS has axes, which do not move with the earth rotation; this frame is known as the inertial frame. In fact, accelerometers and gyroscopes measure their corresponding variables in this frame.

The navigation equations are provided in followings. First, the DCM is updated according to

$$\dot{\mathbf{C}}_b^i = \mathbf{C}_b^i \boldsymbol{\Omega}_{ib}^b \tag{1}$$

Where $\mathbf{C}_b^i$ is the DCM, which is transformed from the body frame to the earth frame and Ω_{ib}^b is the anti-symmetric matrix of the gyroscope output vector. The anti-symmetric matrix of vector **x** can be represented as

$$\mathbf{x} = [x_1, x_2, x_3]^{\mathrm{T}} \Rightarrow \mathbf{X} = \begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix} \tag{2}$$

The velocity and position of vehicle can be calculated as

$$\begin{aligned} &\mathbf{f}^i = \mathbf{C}_b^i \mathbf{f}^b \\ &d/dt(\mathbf{v}^i) = \mathbf{f}^i + \mathbf{g}^i \\ &d/dt(\mathbf{p}^i) = \mathbf{v}^i \end{aligned} \tag{3}$$

Where $\mathbf{f}^b$ is the vector of accelerometers output, $\mathbf{f}^i$ is the vehicle acceleration, $\mathbf{v}^i$ and $\mathbf{p}^i$ are the velocity and position vectors in the inertial reference frame, respectively. The attitude of the Vehicle can be calculated directly from DCM. Using Euler angles (roll, pitch, and yaw) to represent the attitude, navigation equations are:

$$\begin{gathered} \frac{d}{dt}\begin{bmatrix} R \\ P \\ Y \end{bmatrix} = \begin{bmatrix} 1 & \sin(R).\tan(P) & \cos(R).\tan(P) \\ 0 & \cos(R) & -\sin(R) \\ 0 & \sin(R).\sec(P) & \cos(R).\sec(P) \end{bmatrix} . \begin{bmatrix} \Omega_{ib1}^b \\ \Omega_{ib2}^b \\ \Omega_{ib3}^b \end{bmatrix} \\ \frac{d}{dt}\begin{bmatrix} Vx \\ Vy \\ Vz \end{bmatrix} = \begin{bmatrix} \cos(Y).\cos(P) & \cos(Y).\sin(P).\sin(R)+\sin(Y).\cos(R) & -\cos(Y).\sin(P).\cos(R)+\sin(Y).\sin(R) \\ -\sin(Y).\cos(P) & -\sin(Y).\sin(P).\sin(R)+\cos(Y).\cos(R) & \sin(Y).\sin(P).\cos(R)+\cos(Y).\sin(R) \\ \sin(P) & -\cos(P).\sin(R) & \cos(P).\cos(R) \end{bmatrix} \begin{bmatrix} f_1^b \\ f_2^b \\ f_3^b \end{bmatrix} \\ \frac{d}{dt}\begin{bmatrix} Px \\ Py \\ Pz \end{bmatrix} = \begin{bmatrix} Vx \\ Vy \\ Vz \end{bmatrix} \end{gathered} \tag{4}$$

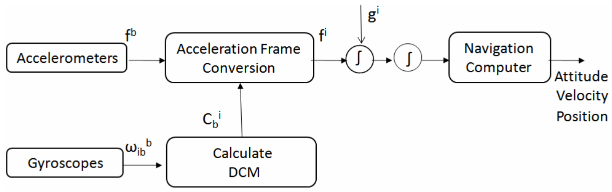

Fig. 1: INS calculations schematic

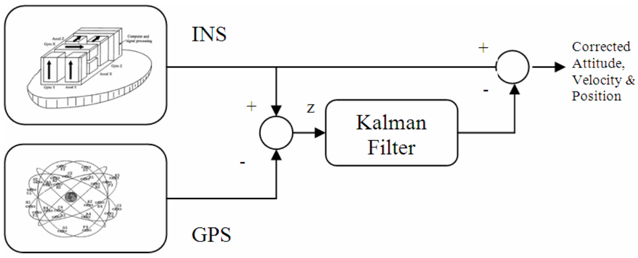

Fig.2: *INS/GPS data integration using KF*

The Euler angles along with the position and velocity of the vehicle represent outputs of the INS. Inputs to this system are the data coming from the inertial sensors. Set of Eq. (4) show that navigation equations are nonlinear. The schematic diagram of inertial navigation calculations is shown in Fig.1 [1].

2. INS errors

There are different error sources in the INS system. The most important sources are [3]:

1. *Inertial sensor errors* (bias, etc.)
2. *Initial attitude, velocity and position error*
3. *Uncertain earth gravity model*

Because INS algorithm involves integral operation of variables over time, any error grows with time. Hence, the navigation accuracy will degrade over the operation time. This is the most important disadvantage of INS. Because of these growing errors, INS needs Navigation-aid systems. In other words, there is need for the absolute information of position, velocity, or attitude of the vehicle [2].

Nowadays, one of the most employed navigation-aid systems is the Global Positioning System (GPS). GPS consists of satellites that send signals to vehicles, which are equipped with GPS receiver, enable vehicles to find their position and velocity. Due to advantages of GPS, integration of INS and GPS in a vehicle can improve performance and overcome many difficulties. However, the main disadvantage of GPS is that there is need for direct line of sight to at least four satellites. There are instances where the GPS signal may not accessible such as in urban areas, tunnels, etc. [3]. To overcome this problem, one approach is that as long as the GPS signal is available, it is used for navigation aiding and the INS is *calibrated* using these data. During the GPS outages, the calibrated INS provides position information by itself. As the gravity model uncertainty can be neglected in many cases, calibration of INS consists of finding errors in inertial sensors and initial navigation errors.

Calibration of INS using the GPS data can be performed using different methods. Kalman filters have been extensively used by researchers for INS/GPS integration. The Kalman Filter (KF) can *estimate* navigation errors as well as parameters of inertial sensor errors. KF performance needs two sets of equations: the process equation and the measurement equation. The process equation is the state-space model of the system with sensors errors as its inputs and velocity, position and attitude errors as its state variables. Moreover, error parameters of inertial sensors are augmented to state variables. Therefore, the error dynamics of inertial sensors must be modeled first. Measurement equation is the relation between states and GPS outputs.

When GPS data are available, states can be estimated and updated. Since error parameters of sensors are components of the state vector, inertial sensors are calibrated as well. Furthermore, the attitude, position, and velocity errors are other part of the state vector. Hence, with estimation of these parameters, navigation errors can be corrected. Fig 2 shows the INS/GPS data integration using the KF.

The classical KF approach has some drawbacks. First, KF needs a state-space model of the process and the measurement. As mentioned earlier, error parameters of inertial sensors (such as the bias) are augmented to the state vector of navigation equations. Moreover, error model of sensors is part of process equation. Therefore, if the model of inertial sensor errors is imprecise, the KF may not yield acceptable results. In fact, modelling of sensors errors is not an easy task in many situations. In this paper, using the KF and Artificial Neural Networks (ANN), a more accurate model of the inertial sensors is provided.

3. Low Cost Inertial Sensors

In recent years, the application of micro-machined inertial sensors that use MEMS (Micro Electro-Mechanical Systems) has grown. This system can reduce sensor components and its electronic circuits to size a chip. These sensors can be made in batch form and production cost be divided between chips. Therefore, the cost of the navigation system can be reduced significantly.

Due to many sources, the error of micro-machined sensors is more than other INS sensors. These sensors are made in small sizes and are very sensitive to environmental variables such as the temperature, pressure, electrical and magnetic fields. Due to these characteristics, micro-machined inertial sensors outputs vary quickly and in many cases vary randomly. Hence, modeling these changes is difficult. Moreover, sensitivity to surrounding conditions adds some new forms of error to these sensors and in many cases the magnitude of error is more than other INS sensors. In fact, derive a suitable stochastic model that reflects sensors operations in different environments and over long period of functioning is difficult. This paper presents more reliable error models for INS sensors [3, 4].

Artificial neural networks are parallel processors that can approximate nonlinear and complicated functions, which are not possible using conventional methods. Neural networks consist of some computational elements (neurons). Every pair of neurons is connected with a synaptic weight (or weight for short). The performance of a neural network is defined by its weights. After training the network with proper data, these weights are adapted to a value such that the network can approximate the required nonlinear function [5]. There are many forms of artificial neural networks; one of the simplest and most important is the Multi-Layer Perceptron (MLP).

In this paper, the Extended Kalman Filter (EKF) is used to train this network. In this approach, weights are assumed as states of a dynamic system and are estimated using the EKF.

Let Γ be the function that relates inertial sensors outputs to true values of these sensors. This function can be dynamic or static. That is, the output of sensors may depend on sensor inputs in past instants

$$\begin{bmatrix} \tilde{\mathbf{f}}^b \\ \tilde{\boldsymbol{\omega}}_{ib}^b \end{bmatrix} = \Gamma\left(\begin{bmatrix} \mathbf{f}^b \\ \boldsymbol{\omega}_{ib}^b \end{bmatrix}\right) \tag{5}$$

Where $\tilde{\mathbf{f}}^b$ and $\tilde{\boldsymbol{\omega}}_{ib}^b$ are actual outputs of sensors, and $\mathbf{f}^b$ and $\boldsymbol{\omega}_{ib}^b$ are true values of the linear acceleration and the rotational velocity, respectively. Obviously, due to the existence of errors in sensors, their outputs are not equal to true values.

If a neural network is trained such that it approximates the inverse of Γ, then sensors can be calibrated using this NN. In this case, the neural network output is equal to approximation of the measured true value (the linear acceleration and the rotational velocity) during navigation. However, training of neural networks requires input/output data of the function. In navigation, true values of the acceleration and velocity are not accessible. In fact, these variables are inputs of navigation equations (Eq. 4) and the attitude, velocity, and position are outputs of these equations. If navigation-aid data are the position of the vehicle, then, the true value of the position is available. Therefore, the actual error that is necessary for training the NN is available when navigation equations are used.

In this paper, the training of NN is performed using EKF. The state variables of this EKF consist of two parts: the first part is the attitude, velocity, and position of the vehicle and the second part is the weights of the NN. Inputs to the system are outputs of inertial sensors. The goal is to estimate state variables of EKF using external information provided by the navigation-aid system. The proposed method is shown in Fig. 3. The input vector to the proposed system is

$$\tilde{\mathbf{u}} = \begin{bmatrix} \tilde{\mathbf{f}}^b \\ \tilde{\boldsymbol{\omega}}_{ib}^b \end{bmatrix} \tag{6}$$

The dynamic of the new system is

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{N}(\tilde{\mathbf{u}}(k), \mathbf{w}(k)) \\ \mathbf{w}(k+1) = \mathbf{w}(k) \end{cases} \tag{7}$$

$$\{\mathbf{y}(k) = \mathbf{g}(\mathbf{x}(k))$$

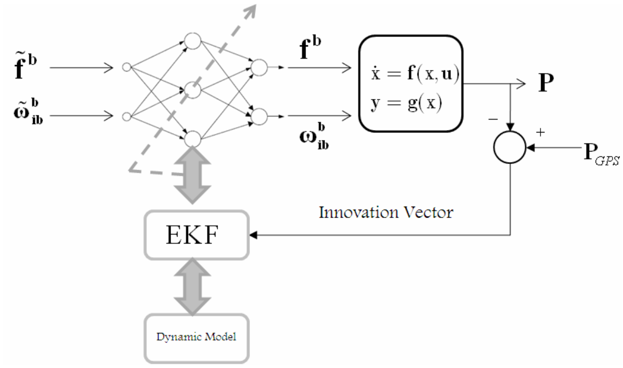

Fig.3: *Proposed data integration scheme*

Where **N** is the nonlinear network between inputs and outputs, **f** is the nonlinear navigation equation and **g** is the measurement function (i.e. the relation between external data and state variables). By determining weights in the NN, the input/output mapping of inertial sensors and their calibration are defined [6, 7]. When the external information is available, EKF estimates states of Eq. 7. In this situation, EKF is in the *time update/measurement update* mode and the neural network is in the training mode. Estimating weights leads to calibration of sensors. Other states provide the attitude, velocity, and position of the vehicle. However, as mentioned earlier, the navigation-aid system is not available at all time. During GPS outages, the neural network mode changes from the "training mode" to the "using mode" and EKF works in *time update* mode. In this situation, outputs of inertial sensors are set as network inputs and an approximation of the true linear acceleration and rotational velocity are obtained as network outputs. These outputs are inputs to navigation equations. Solving navigation equations yields the corrected attitude, velocity, and position of the vehicle. This procedure is called the Artificial Neural Network/KF (ANN-KF) method in this paper. Using this method, inertial sensors can be calibrated during the navigation and find navigation variables without the need to model errors of inertial sensors. In fact, error models are approximated online using the NN. Fig. 3 shows the proposed structure. In this figure, the block designated with "dynamical model" is the model used by EKF (Eq. (7)).

4. Simulation Results

The performance of the proposed method will be shown through simulations. Assume that six inertial sensors have constant bias and scale factor errors. However, for the modeling, it is assumed that only bias errors exist (wrong modeling). Two NNs are employed to approximate the mapping of the sensors: one NN for accelerometers and the other NN for gyroscopes. Each

NN has three inputs (outputs of inertial sensors) and three outputs (approximation of actual linear acceleration and rotational velocity, respectively). Each NN has two neurons in the hidden layer with logistic sigmoid activation function and three neurons in the output layer with linear activation function. It is assumed that the navigation-aid system provides the required information in the form of vehicle position in north-east-down directions. Moreover, it is assumed that this information is updated every second with the accuracy of one meter. First, it is assumed that in the time interval of 0-800 seconds, the navigation-aid data is available. During this time, EKF trains the NN. Fig. 4 shows the changes occurred in the weights of the NN for accelerometers. The weights in the Gyroscopes NN converge similarly.

As was mentioned before, the EKF in the proposed method estimates navigation variables too. Figs. 5-7 show the errors in azimuth angle, the north velocity, and the east position of the EKF and the proposed ANN-EKF method. As these figures show the conventional EKF cannot cope with the false error modeling and its state variable diverges (the EKF is model dependent) while the proposed ANN-EKF method can still provide acceptable results.

Next, it is assumed that the navigation-aid system is not available during the time interval of 800-1200 seconds. Figs. 8-10 show the error of the azimuth angle, north velocity, and east position during 400 seconds of GPS unavailability. During these times, NNs are trained and the last estimated values of weights are used for modeling approximation. Although the navigation error is growing in both methods, nevertheless, the proposed method can tolerate the navigation-aid outage much better than the EKF alone.

Next simulation is to verify that if navigation-aid data become available after 1200 seconds, is it possible to continue data integration or not. Figs 11 to 13 show error in yaw angle, north velocity and east position, if GPS data connects again in 1200th second. This figs show clearly that data integration can continue after reconnecting navigation-aid system.

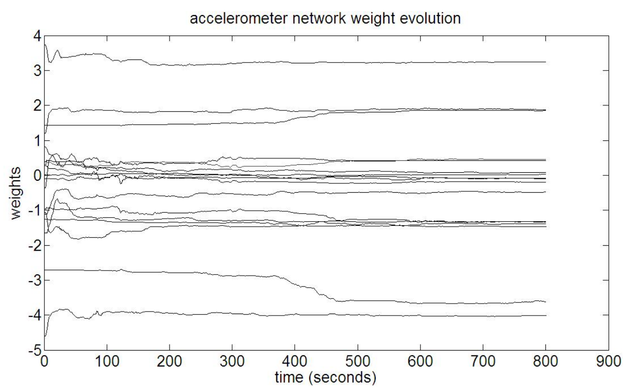

Fig.4: *Accelerometer network weight evolution*

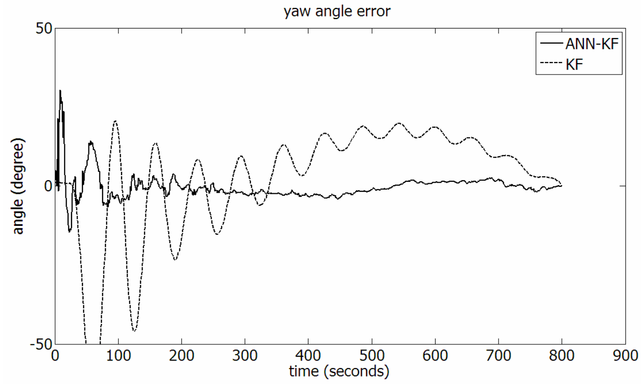

Fig.5: *Yaw angle error during data integration*

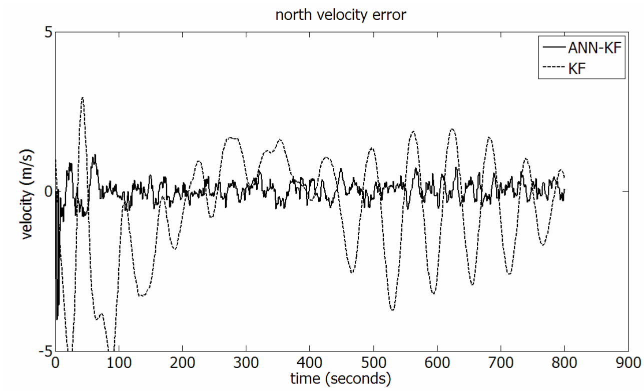

Fig.6: *North velocity error during data integration*

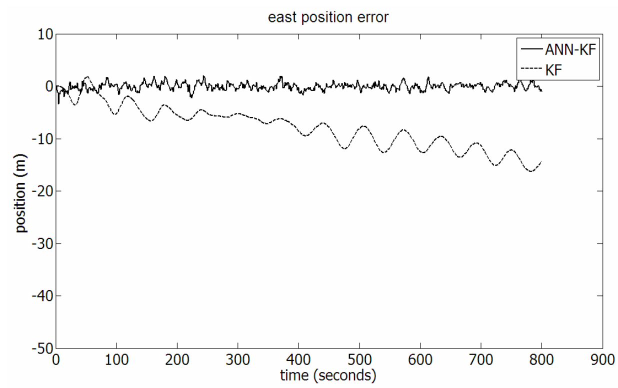

Fig.7: *East position error during data integration*

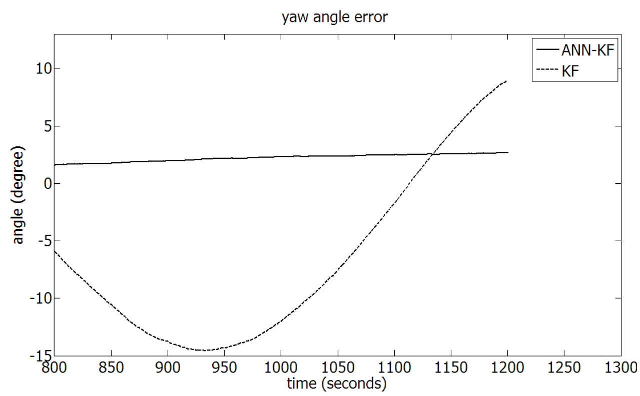

Fig.8: *yaw angle error during GPS outage*

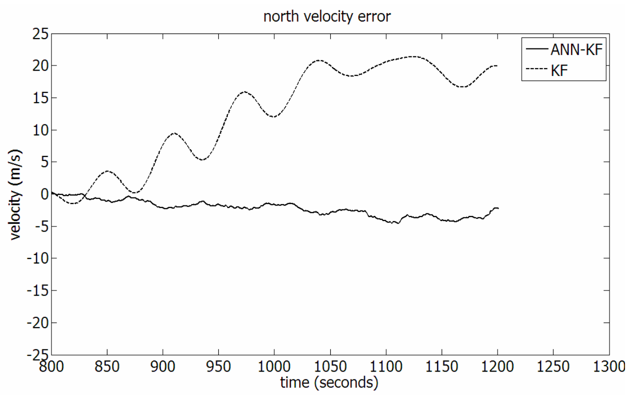

Fig.9: *north velocity error during GPS outage*

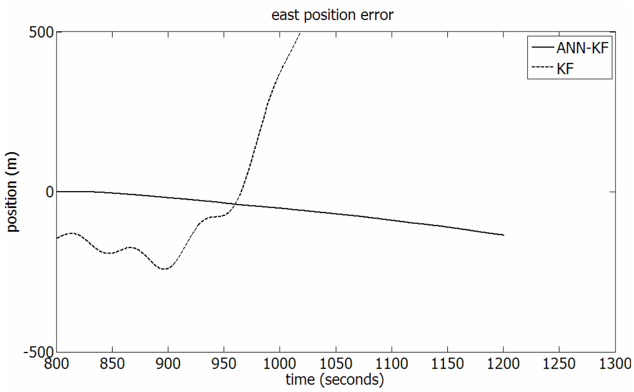

Fig.10: *east position error during GPS outage*

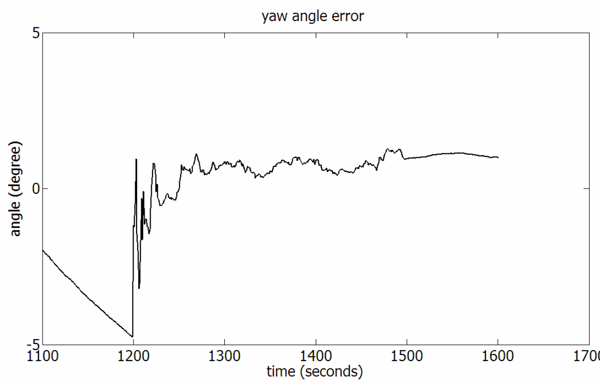

Fig.11: *yaw angle error after reconnecting GPS*

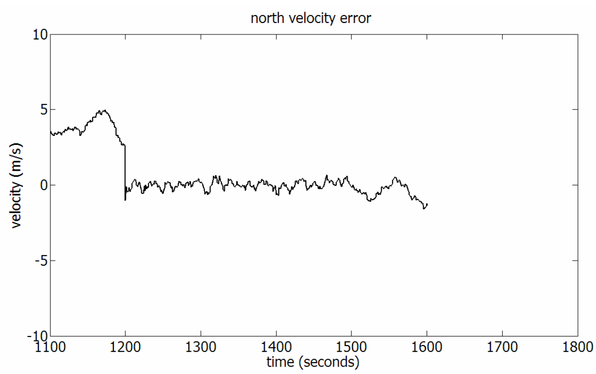

Fig.12: *north velocity error after reconnecting GPS*

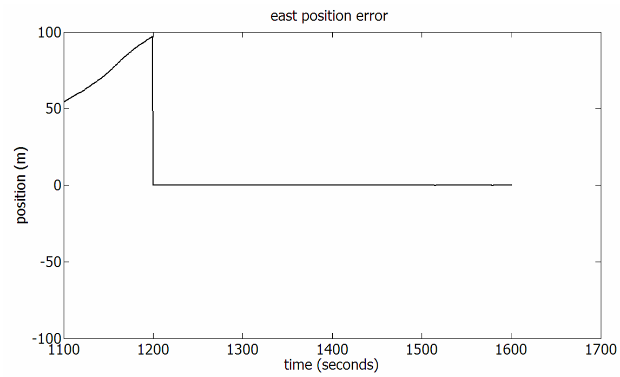

Fig. 13: *east position error during GPS outage*

5. Conclusions

In this paper, a new method for online calibration of inertial sensors using Kalman filter and artificial neural networks was proposed. The states of Kalman filter are synaptic weights of the NNs and the attitude, velocity, and position of the vehicle in the reference frame. Two NNs were employed to model the inertial navigation sensors: accelerometers and gyroscopes. These networks were trained when the navigation-aid system (e.g. GPS) is available. During the outage of the navigation-aid system, no training of NNs was performed and these networks provide an approximation of the actual position, velocity, and attitude of the vehicle. Simulation results were compared with the EKF-alone system and it was showed that the proposed method could provide good modeling of the inertial sensors even when false sensor errors were provided to the networks. Moreover, it could cope with the navigation-aid outage for relatively long navigation times.

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