Research on Integrated Navigation Algorithm Based on Radial Basis Function Neural Network

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Abstract. The Qinghai-Tibet Railway is located on the Qinghai-Tibet Plateau in China. Due to its harsh climatic conditions and geographic environment, the line currently uses the Global Position System (GPS) to achieve train positioning. However, the navigation satellites are easily blocked by obstructions such as tunnels, resulting in a decrease in positioning accuracy. The conventional solution is to use multiple sensors such as an inertial navigation system (INS) for data fusion. But in the INS/GPS integrated navigation system, when the GPS signal is lost, the navigation accuracy will still decrease. In order to solve this problem, this paper proposes a radial basis function (RBF) neural network-assisted integrated navigation filtering algorithm. When the two systems are working normally, the measured raw information is used to train the RBF neural network. When the GPS fails, the measured and calculated values of the inertial navigation system are input to the trained network model to obtain the predicted error value, which is corrected to the inertial navigation system to obtain the final navigation information. The MATLAB simulation results show that when the short-term GPS information is missing, the integrated navigation system assisted by the RBF neural network has better estimation accuracy.

1. Introduction

In the navigation field, the most widely used systems are the Inertial Navigation System (INS) and the Global Position System (GPS). The advantages and disadvantages of the two systems are complementary to a certain extent. The inertial navigation system has strong anti-interference ability and high accuracy in a short time, but its positioning accuracy will continue to diverge as time increases. For the satellite navigation system, the structure and communication method of the system make the system vulnerable to external signal interference, and in the presence of obstructions, signal interruption is very easy to occur, but under long-term navigation operations, it can maintain relatively stable accuracy. Combining the two systems organically can overcome their own shortcomings, compensate each other, and give full play to their respective advantages [1].

Among the data fusion algorithm of INS/GPS integrated navigation system, the Kalman filter algorithm and the improved filter algorithm based on it are the most researched and applied by scholars. Simanek [2] proposed a data fusion method based on extended Kalman filtering. The dead reckoning algorithm is used to calculate the navigation information such as the position and direction of the carrier. Saadeddin [3] proposed a low-cost car navigation and status detection system. This system uses speed sensors, INS and GPS to collect information through extended Kalman filtering and...
extended information filtering to obtain highly dynamic vehicle position, speed and other navigation information. Ryu [4] used extended Kalman filter and unscented Kalman filter for INS/GPS integration and obtained more accurate navigation results.

The combination of emerging artificial intelligence methods and integrated navigation systems has also been widely studied and applied. Aiming at the integrated navigation system under the high dynamic and strong interference environment, Xiangwen Bai [5] proposed an Elman neural network-assisted integrated navigation federated filtering algorithm, which uses the Elman neural network model to predict when the satellite signal is out of lock. Their MATLAB simulation experiments verify that the algorithm can suppress the accumulation of inertial navigation errors when satellite signals are lost. Tianmin Deng [6] proposed an IMU/GPS integrated navigation method based on nonlinear adaptive recurrent neural network for high-precision positioning of intelligent networked vehicles. Adusumilli [7] applied the random forest regression method to the integration of INS and GPS as an accurate and reliable navigation solution. It is verified by experiments to simulate GPS interruption that this method can reduce the position error by 24.0%~56.0%. Xiaoyan Li [8] proposed an integrated navigation algorithm based on BP neural network assistance. Tests on sports cars proved that the speed accuracy of this method is within 0.2m/s, the position accuracy is within 25 meters. Minghui Qiang [9] combined RBF neural network and federal Kalman Filter to effectively eliminate the influence of external interference and model uncertainty on the system.

This paper combines the RBF neural network in the neural network with the traditional Kalman filter, and proposes a data fusion algorithm that can maintain the navigation accuracy of the integrated navigation system when the GPS signal is lost.

2. Radial basis function neural network

2.1. The structure of RBF neural network

The RBF neural network is a feedforward network with a three-layer structure, which mainly includes an input layer, a hidden layer and an output layer. Among them, the first layer is the input layer, including the number of input nodes, and the number is generally determined by the dimension of the input; the second layer is the hidden layer, and the number of nodes in the hidden layer is determined by the complexity of the research problem. The transfer function of the layer nodes is the radial basis function, and the Euclidean distance between the center points is a radially symmetric and attenuated non-negative nonlinear function; the third layer is the output layer, in the output layer, the number of nodes is equal to the output Dimension, the result of the output layer is the linear weighted sum of the output of each unit in the hidden layer [10].

![Figure 1. RBF neural network topology.](attachment:image.png)
Where \( x_1, x_2, \ldots, x_n \) are the input of the network, \( n \) is the dimension of the input layer, \( \varphi(x) \) is the radial basis function, \( w \) is the output weighting matrix, the radial basis function is generally a Gaussian kernel function.

\[
\varphi_i(x) = \exp\left(-\frac{||x-c_i||^2}{2\sigma_i^2}\right), i = 1, 2, \ldots, p
\]  

\[
y_j = \sum_{i=1}^{p} w_{ij} \varphi_i(x), j = 1, 2, \ldots, m
\]

Where \( x \) is the input, \( c_i \) is the center vector of the \( i \)th radial basis function, \( \sigma_i \) represents the width of the \( i \)th hidden node, \( p \) and \( m \) respectively represent the number of hidden nodes and output nodes, \( w_{ij} \) represents the weight from the \( i \)th hidden node to the \( j \)th output node.

RBF neural network has only one hidden layer, its network structure complexity is reduced, and the training difficulty of the network is reduced at the same time. The compact topology structure allows its own structural parameters to achieve separate learning and speed up convergence. Improve the generalization ability of the network. These advantages allow RBF neural networks to approximate arbitrary nonlinear functions. Therefore, this paper chooses RBF neural network to assist the INS/GPS integrated navigation system. Figure 1 shows the commonly used structure of RBF neural network.

2.2. The establishment of RBF neural network

First, select the data of the integrated navigation simulation experiment stage where the GPS is working normally, and use the INS system's east, north and sky angular velocities, acceleration in the three directions and the calculated position information as the input of the neural network.

The entire simulation experiment lasts 600 seconds, the Kalman filter period is 1 second, and 500 sets of data from 0 to 500 seconds are selected as training samples. Use MATLAB’s built-in radial basis neural network function to quickly build a network model and train the network. The training parameters are as follows: the expected error of the training network is less than \( 10^{-4} \), the radial basis function distribution density is 10 and the RBF neural network is established and trained. Finally, the trained network model is used to compensate the speed and position for the 100 seconds time period when the GPS signal is lost.

3. Scheme design of integrated navigation system assisted by RBF neural network

3.1. INS/GPS integrated navigation system algorithm

The INS/GPS integrated navigation system adopted in this paper uses the northeast sky geographic coordinate system as the navigation coordinate system. The three-axis attitude angle error \( \Delta \varphi_E \), three-axis speed error \( \Delta v_E \), position error \( \Delta p_E \), gyroscope constant drift \( \varepsilon_g \), and accelerometer constant drift \( \varepsilon_a \) measured and calculated by INS are selected as the state vector of the integrated navigation system. The state vector can be expressed as equation (3).

\[
X = [\Delta \varphi, \Delta v, \Delta \varphi_E, \Delta v_E, \Delta \dot{p}_E, \Delta \varphi_N, \Delta v_N, \Delta \dot{p}_N, \Delta \varphi_U, \Delta v_U, \Delta \dot{p}_U, \varepsilon_g, \varepsilon_{gy}, \varepsilon_{gx}, \varepsilon_{ax}, \varepsilon_{ay}]^T
\]  

Expand the equation to get the following form.

\[
X = [\Delta \varphi_E, \Delta \varphi_N, \Delta \varphi_U, \Delta v_E, \Delta v_N, \Delta v_U, \Delta \dot{p}_E, \Delta \dot{p}_N, \Delta \dot{p}_U, \varepsilon_{gy}, \varepsilon_{gx}, \varepsilon_{ax}, \varepsilon_{ay}]^T
\]  

Where E, N, U represent the three directions of east, north and sky, \( \Delta \varphi_E, \Delta \varphi_N, \Delta \varphi_U \) are the attitude angle error in three directions \( \Delta v_E, \Delta v_N, \Delta v_U \) are the speed error in three directions \( \Delta \dot{p}_E, \Delta \dot{p}_N, \Delta \dot{p}_U \),
$\Delta p_H$ represent longitude, latitude and elevation error, $\varepsilon_{gx}$, $\varepsilon_{gy}$, $\varepsilon_{gz}$ are the gyro drift along the x, y, z axis of the carrier coordinate system, $\varepsilon_{ax}$, $\varepsilon_{ay}$, $\varepsilon_{az}$ are the acceleration drift along the x, y, z axis of the carrier coordinate system.

The state equation and measurement equation of the system can be expressed as equation (5).

$$
\begin{align*}
X_k &= \Phi_{k,k-1}X_{k-1} + \Gamma_{k,k-1}W_{k-1} \\
Z_k &= H_k X_k + V_k
\end{align*}
$$

(5)

Where $X_k$ is the system state vector, $\Phi_{k,k-1}$ is the one-step transition matrix of the system, $\Gamma_{k,k-1}$ is the system noise allocation matrix, $W_{k-1}$ is the system noise vector, $Z_k$ is the measurement vector, $H_k$ is the measurement matrix, $V_k$ is the measurement noise vector. Both $W$ and $V$ are Gaussian white noise sequences and are not correlated.

3.2. Integrated navigation system assisted by RBF neural network

The RBF neural network-assisted INS/GPS integrated navigation structure designed in this paper mainly includes two stages. The first stage is the period of time when the normal GPS signal is not interrupted from 0 to t. The INS and GPS systems are loosely coupled to perform data fusion under the Kalman filter calculation, and the resulting processed data is used as Final navigation information. At the same time, at this stage, the RBF neural network is trained using the navigation information solved by the single system of the inertial navigation system and the filtered fusion data. The training process is as follows: the angular velocity $\omega_{ins}$ collected by the INS system from 0 to t when the GPS signal is not interrupted, speed information $v_{ins}$ and position information $p_{ins}$ obtained by the calculation are used as the training input data of the neural network. The error $\Delta p$, $\Delta v$ between the position $p_{ins/gps}$ and speed $v_{ins/gps}$ calculated by the combined system and the position $p_{ins}$ and speed $v_{ins}$ calculated by the pure INS navigation is used as the expected output of the RBF neural network. The RBF neural network is trained. The second stage: after time t, GPS out of lock and GPS signal is lost. Only the INS in the combined system works normally, the Kalman filter fails, and the system is transformed into a prediction mode. At this time, the neural network takes the INS speed $v_{ins}$ and position $p_{ins}$ information as input. Through the trained neural network, the speed and position errors are predicted, the INS output is compensated with the predicted data, and the compensated data is used as the navigation data of the carrier.

![Diagram](figure2.png)

Figure 2. RBF-assisted integrated navigation system structure.

4. Simulation and analysis

This paper uses the MATLAB platform and the INS toolbox to generate simulated motion trajectories, and conducts subsequent experimental analysis on the basis of the simulated trajectory. In the
simulation trajectory design, in order to make it closer to the real situation, consider the gyroscope, accelerometer and the relative error of the global satellite navigation system. The main considerations are the constant zero offset error and random walk error. The specific parameters are as follows: the gyroscope zero offset is $0.05^\circ/h$, and the gyroscope angle random walk is $0.002^\circ/\sqrt{h}$. The accelerometer constant value deviation is $4.9\times10^{-3}\text{m/s}^2$, and the accelerometer speed random walk is $4.9\times10^{-5}\text{m/s}^2$. The system simulation time is 600 seconds.

When the system only has the INS system working alone, the positioning error is shown in Figure 3. Due to the INS components themselves, the error accumulates and diverges over time. It can be seen from the figure that the longitude and latitude in pure inertial navigation mode, the error reached 600 meters and 240 meters respectively at the time of 600 seconds. The pure inertial navigation system cannot provide navigation information that meets the accuracy requirements during long-term navigation operations.

![Figure 3. Position error of pure inertial navigation system.](image)

In the simulation process, the GPS is set to lose lock from time $t=500$ seconds. Before this time, the integrated navigation system can maintain a normal working state. The system uses Kalman filtering to perform data fusion and output navigation parameters, which are collected by two subsystems at the same time. The data is trained on the neural network with the results of Kalman filtering. After the GPS out of lock, the output of the neural network is used to compensate the INS, and the experimental results are shown in Figure 4-Figure 7.

Figure 4 and Figure 5 show the eastward and northward speed drifts with the help of the RBF neural network after the GPS signal is lost in the simulation process. In 100 seconds after the GPS signal lost, the maximum drift of the east and north speeds reaches $0.16\text{m/s}$ and $0.26\text{m/s}$.

It can be known from the experimental results of Figure 6 and Figure 7 that within 0 to 500 seconds, the GPS signal is not out of lock at this time, and the integrated navigation system obtains good positioning accuracy through the Kalman filter, and the position error is stable within 5 meters. Set the GPS interrupt at $t=500$ seconds. At this time, only the inertial navigation system is working alone. From Figure 3, it can be seen that the positioning accuracy of the system will gradually diverge over time. It is estimated that after 100 seconds, the cumulative position error will reach 50 meters. At $t=500$ seconds, the trained neural network is used to compensate the position and speed of the INS navigation information. After the INS is compensated by the neural network, the maximum position error of longitude and latitude is 4.17 meters and 2.11 meters.
The root mean square error of the three schemes is shown in Table 1. Under the Kalman filter data fusion of the integrated navigation system, the accuracy of east and north speed, longitude and latitude has been significantly improved compared with pure inertial navigation system. In the last 100 seconds of the simulation, with the assistance of RBF NN, the system has better restrained the error growth of the pure inertial navigation system and made the deviation stable under reliable data accuracy. The RBFNN-assisted Kalman filtering method proposed in the article guarantees the stability and accuracy of the integrated navigation system as a whole.

| RMSE       | East speed/(m/s) | North speed /(m/s) | Longitude /(m) | Latitude/(m) |
|------------|------------------|--------------------|----------------|--------------|
| INS        | 0.6187           | 1.0659             | 361.7413       | 121.4713     |
| Kalman filter | 0.0924         | 0.1687             | 2.6318         | 1.5157       |
| RBFNN      | 0.0861           | 0.1481             | 2.5368         | 1.3234       |

5. Conclusion
This paper focuses on the situation that the traditional INS/GPS integrated navigation system causes the temporary lack of satellite signal under the unfavorable conditions such as tunnel occlusion, which leads to the decrease of system accuracy and stability. Combining radial basis function neural network with traditional Kalman filter, a RBF neural network-assisted INS/GPS integrated navigation system
information fusion scheme is proposed. Through MATLAB simulation experiments, it is verified that this method has a certain improvement in accuracy and stability compared with pure inertial navigation system, and it can restrain the divergence of the system in a short time.

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