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Research Article

Application of Elman Neural Network Based on Genetic Algorithm in Initial Alignment of SINS for Guided Projectile

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The purpose of this paper is to present an in-flight initial alignment method for the guided projectiles, obtained after launching, and utilizing the characteristic of the inertial device of a strapdown inertial navigation system. This method uses an Elman neural network algorithm, optimized by genetic algorithm in the initial alignment calculation. The algorithm is discussed in details and applied to the initial alignment process of the proposed guided projectile. Simulation results show the advantages of the optimized Elman neural network algorithm for the initial alignment problem of the strapdown inertial navigation system. It can not only obtain the same high-precision alignment as the traditional Kalman filter but also improve the real-time performance of the system.

1. Introduction

The initial alignment of the strapdown inertial navigation system (SINS) provides initial values in order to complete the navigation calculations task, including initial position, initial velocity, and initial attitude. Due to the accumulation of initial errors in navigation calculations, it is necessary to control the initial alignment errors within a certain range, especially the initial attitude error.

The main task of the initial alignment is to determine the initial direction cosine matrix, namely, the attitude matrix C_b^n, which is transferred from the body coordinate (b-coordinate) to the navigation coordinate (n-coordinate). According to the movement state of the carrier, the initial alignment can be divided into static base alignment and moving base alignment. Many researches on static base alignment technology are discussed and studied [1–4], but for the guided projectile studied in this paper, the velocity and attitude dynamically change, so it is necessary to complete the alignment under the condition of the movement base. Thus, the gravitation acceleration and the gyro-measured value of the earth's rotation cannot be simply used to calculate the attitude matrix C_b^n [5].

The process of alignment can be divided into two stages: coarse alignment and fine alignment. The coarse alignment obtains a rough attitude matrix C_b^n, which provides a basis for subsequent fine alignment. This stage requires a lower precision but does so quickly [6, 7]. The traditional initial coarse alignment algorithm is calculated under the static state of the carrier. However, for the guided projectile, the initial alignment is started in the motion process, which means in-flight alignment, and the carrier is also accompanied by high-speed rotation during the high-speed flight. The traditional initial alignment algorithm is no longer applicable. For the proposed initial alignment algorithm in this paper, the coarse alignment algorithm uses the equations of specific force and the combination of GPS information with geomagnetic information to obtain the rough attitude matrix C_b^n. The detailed process is derived in [8] and no longer described here; only the fine alignment algorithm is discussed in this paper.

Fine alignment is carried out on the basis of the estimated attitude matrix from coarse alignment. By processing the output information of the inertial device, the real-time value of the misalignment angle is estimated. The attitude matrix from coarse alignment is replaced by the real-time updated attitude matrix, and then the accurate attitude matrix is obtained. Fine alignment mostly uses the Extended Kalman Filter (EKF) [9] and the Unscented Kalman Filter (UKF) [10] algorithms. At the same time, there are also improved filtering methods based on these two Kalman filters, such as Extended Particle Filter (EPF) algorithm [11], Unscented Particle Filter (UPF) algorithm [12], Adaptive Unscented Kalman Filter (AUKF) algorithm [13], and high-degree Cubature Kalman Filter (CKF) [14].

In recent years, with the rapid development of neural network technology, researchers have used the theory and idea of artificial neural network to solve the problems, which are difficult to be solved using traditional control theory [15]. Neural network has a good function approximation, real-time performance, and robustness. Thus, it can be used instead of a Kalman filter to solve the initial alignment of SINS. L. Vargasmeléndez et al. successfully combined neural network with standard linear Kalman filtering of inertial navigation system (INS) [16]. X. L. Wang and R. Zhang et al. studied the weight updating of multilayer neural network learning algorithm based on the principle of EKF and obtained the same precision as EKF [17–19]. Y. H. Liu et al. introduced the neural network based on the UKF [20]. D. Liu and T. Zhang et al. used a Wavelet Neural Network (WNN) in the method [21, 22]. However, as the carriers that have been studied before are mostly static-based systems, the selected neural network structures are mostly feedforward structures. The research methods above are not suitable for the proposed carrier of this paper. The feedback neural network Elman network will be used for the real-time dynamic characteristics of the guided projectile studied in this paper.

The Elman feedback network can meet the dynamic characteristics of the dynamic systems, but it is easy to fall into the local minimum value in the search of solutions. Therefore, it is necessary to combine an optimization algorithm to complete the global optimizing. The genetic algorithm (GA), by imitating the Mendel genetic variation theory, maintains a good structure in the iterative process and searches for a better structure. It is an optimized searching method that does not rely on specific problems. It can be used to optimize the structure of neural networks, which are difficult to express in function forms. Combining the genetic algorithm with the neural network can not only guarantee the real-time performance of the initial alignment but also optimize the operation. The backpropagation (BP) network and the Radial Basis Function (RBF) network optimized using GA have already been widely demonstrated [23, 24].

In this paper, an application of the Elman neural network based on the GA is studied to obtain the initial alignment of the SINS for a guided projectile and, moreover, to solve the problems of real-time performance and robustness when using traditional Kalman filtering algorithm in the initial fine alignment. This method has the advantages of high precision and fast calculations time. First, the nonlinear error models of initial alignment of SINS are built, and then the Elman neural network models of initial alignment are established. Then, the optimization processes of neural network based on GA are obtained. Finally, the simulation is carried out, and the feasibility of the proposed method is proved by the data comparison.

2. Nonlinear Error Model of Initial Alignment of SINS

The establishment of accurate error equations is the basis of initial alignment using various filtering techniques. In this paper, velocity errors, misalignment angle errors, and position errors are used as error models. We chose the East-North-Up (ENU) geographic coordinate (t-coordinate) as the navigation coordinate (n-coordinate) of the guided projectile in-flight control. In view of the application precision of MEMS, make the earth default into round ball, which is $R_M = R_N = R$. Meanwhile, the influences of calibration coefficient error and installation error are far smaller than misalignment angle error; the model established below ignores them.

Three position errors of longitude, latitude, and height; three velocity errors of east, north, and up directions; three misalignment angles of pitch, roll, and yaw; three directions of gyro error; and three accelerometer errors are selected as state variables for the in-flight initial alignment of SINS: $X(k) = [\delta L \;\; \delta\lambda \;\; \delta h \;\; \delta V_E \;\; \delta V_N \;\; \delta V_U \;\; \varphi_E \;\; \varphi_N \;\; \varphi_U \;\; \varepsilon_E \;\; \varepsilon_N \;\; \varepsilon_U \;\; \nabla_E \;\; \nabla_N \;\; \nabla_U]^T$. The measurement variables select $Z(k) = [\Delta L \;\; \Delta\lambda \;\; \Delta h \;\; \Delta V_E \;\; \Delta V_N \;\; \Delta V_U]^T$, which are the location differences and velocity differences between the SINS calculation and GPS receiver in real time, that is,

$$\begin{aligned} \Delta L &= L_{INS} - L_{GPS} \\ \Delta\lambda &= \lambda_{INS} - \lambda_{GPS} \\ \Delta h &= h_{INS} - h_{GPS} \\ \Delta V &= V_{INS} - V_{GPS}. \end{aligned} \tag{1}$$

The discrete system state equation and measurement equation for state estimation can be written as follows:

$$\begin{aligned} X(k) &= \phi(k, k-1)\, X(k-1) + \Gamma(k-1)\, W(k-1) \\ Z(k) &= H(k)\, X(k) + V(k), \end{aligned} \tag{2}$$

where $\phi(k, k-1)$ is the transition matrix from time k-1 to time k, $\Gamma(k-1)$ is the noise driving matrix, $W(k$-1$)$ is the Gaussian random process noise with mean 0 of SINS, $H(k)$ is the measurement matrix, and $V(k)$ is the Gaussian random measurement noise with mean 0 of SINS.

According to the derivation and simplification of the specific force equation, the expressions of the error models are obtained as follows.

2.1. Misalignment Angle Error Model

$$\begin{aligned} \dot{\varphi}_E = &-\frac{\delta V_N}{R+h} + \left(\omega_{ie}\sin L + \frac{V_E}{R+h}\tan L\right)\varphi_N \\ &- \left(\omega_{ie}\cos L + \frac{V_E}{R+h}\right)\varphi_U + \varepsilon_E \end{aligned}$$

$$\begin{aligned}\dot{\varphi}_N &= \frac{\delta V_E}{R+h} - \omega_{ie}\sin L\delta L \\ &\quad - \left(\omega_{ie}\sin L + \frac{V_E}{R+h}\tan L\right)\varphi_E - \frac{V_N}{R+h}\varphi_U \\ &\quad + \varepsilon_N \\ \dot{\varphi}_E &= \frac{\delta V_E}{R+h}\tan L + \left(\omega_{ie}\cos L + \frac{V_E}{R+h}\sec^2 L\right)\delta L \\ &\quad + \left(\omega_{ie}\cos L + \frac{V_E}{R+h}\right)\varphi_E + \frac{V_N}{R+h}\varphi_N + \varepsilon_U,\end{aligned} \tag{3}$$

where ω_{ie} is the rotational speed of the Earth. ε is the gyro-error and the subscripts denote direction; this paper models this error based on the first-order Markov process:

$$\dot{\varepsilon}_g^r = -\frac{1}{T_{gr}}\varepsilon_g^r + w_g^r, \tag{4}$$

where T_{gr} is correlation time, ε_g^r is gyro-random drift error, and w_g^r is driving white noise of random drift and its variance equals $2/T_{gr}R(0)$. $R(0)$ is the mean square value of the Markov process. When the mean value of process is zero, it equals the variance of gyro-drift.

2.2. Velocity Error Model

$$\begin{aligned}\delta\dot{V}_E &\\ &= f_N\varphi_U - f_U\varphi_N + \left(\frac{V_N}{R+h}\tan L - \frac{V_u}{R+h}\right)\delta V_E \\ &\quad + \left(2\omega_{ie}\sin L + \frac{V_E}{R+h}\tan L\right)\delta V_N \\ &\quad - \left(2\omega_{ie}\cos L + \frac{V_E}{R+h}\right)\delta V_U \\ &\quad + \left(2\omega_{ie}\cos L V_N + \frac{V_E V_N}{R+h}\sec^2 L + 2\omega_{ie}\sin L V_U\right)\delta L \\ &\quad + \nabla_E \\ \delta\dot{V}_N &\\ &= f_U\varphi_E - f_E\varphi_U - 2\left(\omega_{ie}\sin L + \frac{V_E}{R+h}\tan L\right)\delta V_E \\ &\quad - \frac{V_N}{R+h}\delta V_U - \frac{V_U}{R+h}\delta V_N \\ &\quad - \left(2\omega_{ie}\cos L + \frac{V_E}{R+h}\sec^2 L\right)V_E\delta L + \nabla_N \\ \delta\dot{V}_U &\\ &= f_E\varphi_N - f_N\varphi_E + 2\left(\omega_{ie}\cos L + \frac{V_E}{R+h}\right)\delta V_E \\ &\quad + 2\frac{V_N}{R+h}\delta V_N - 2\omega_{ie}\sin L V_E\delta L + \nabla_U,\end{aligned} \tag{5}$$

where f is specific force from accelerometer with subscripts denote direction.

In this velocity error model, ∇ is the accelerometer error. It is also modeled based on the first-order Markov process:

$$\dot{\nabla}_a^r = -\frac{1}{T_{ar}}\nabla_a^r + w_a^r. \tag{6}$$

The meaning of the accelerometer error in the Markov process is defined the same as the gyro-error.

2.3. Position Error Model

$$\begin{aligned}\delta\dot{L} &= \frac{\delta V_N}{R+h} \\ \delta\dot{\lambda} &= \frac{\delta V_E}{R+h}\sec L + \frac{V_E}{R+h}\sec L\tan L\delta L \\ \delta\dot{h} &= \delta V_U\end{aligned} \tag{7}$$

After obtaining the estimated errors, we can correct attitude matrix C_b^n in real time. The correction equation is

$$C_b^n = [\mathrm{I} - \delta\varphi\times]\,\widehat{C}_b^n \tag{8}$$

$$\delta\varphi\times = \begin{bmatrix} 0 & -\delta\varphi_U & \delta\varphi_N \\ \delta\varphi_U & 0 & -\delta\varphi_E \\ -\delta\varphi_N & \delta\varphi_E & 0 \end{bmatrix}, \tag{9}$$

where $\widehat{C}_b^n$ denotes rough attitude matrix from coarse initial alignment and $\delta\varphi\times$ is antisymmetric matrix of the estimated misalignment angle errors.

3. Elman Neural Network Model of Initial Alignment

According to the error models established in the previous section, the state estimation can be obtained by a certain filtering method and then has feedback to eliminate the errors. Since the running time of the Kalman filter is directly proportional to the cubic of the system's order, it is difficult to ensure the real-time performance when the system's order is high. The neural network has a self-learning function, can approximate any nonlinear function, and has fast data processing. Therefore, the neural network can be used instead of the Kalman filter for the initial fine alignment of SINS.

The typical structure of a multilayer neural network is composed of three layers of artificial neural nodes, namely, the input layer, the hidden layer, and the output layer. The number of neurons in the input layer corresponds to the dimension of the input information of the system. All of the neurons exported from the input layer are weighted with thresholds by a nonlinear transmission function and then imported to the hidden layer. The input of each neuron node in the output layer is calculated and weighted by the output of all nodes in the hidden layer [25]. However, the main parameters of in-flight alignment are time-varying. In order to realize the identification of the dynamic system, the historical output of the system can only be added to the input vector by adding external delay if the general forward neural network structure is adopted. It increases the dimension of the input vector, thus leading to an increase of the entire system's order and a decrease of the convergence rate. Therefore, a feedback multilayer neural network is needed. An Elman neural network is used in this paper.

The Elman neural network, which was proposed by Jeffrey L. Elman in 1990, is a typical model of a feedback neural network, which has very strong computing power. It generally consists of four layers: the input layer, the hidden layer, the connection layer, and the output layer. Compared with the forward neural networks such as a BP neural network, there is an extra connection layer that receives a feedback signal from the hidden layer, which is used to memorize the output value of the previous moment from the hidden layer neurons. After delay and storage, the signal is then reentered into the hidden layer. This method of self-connection makes the data of the historical state sensitive. The addition of internal feedback network improves the ability to process dynamic information, to achieve the purpose of dynamic modeling.

It is assumed that the Elman neural network has a m dimension input vector $x_i(i = 1, 2, \ldots, m)$, l dimension hidden layer neurons $O_h(h = 1, 2, \ldots, l)$, l dimension connection layer neurons $C_h(h = 1, 2, \ldots, l)$, and n dimension output vector $y_i(i = 1, 2, \ldots n)$. We use w^{ml}, w^{ln}, and w^{ll} to represent the weight between the input layer and the hidden layer, the hidden layer and the output layer, and the hidden layer and the connection layer, respectively. The output of the *h-th* neuron node of the connection layer is

$$C_h(k) = O_h(k-1), \tag{10}$$

where k and k-1, respectively, indicate the time at present and the time at the step delay. The input information of the *h-th* neuron node of the hidden layer is

$$I_h(k) = \sum_{i=1}^{m} w_{ih} x_i(k) + \theta_h \tag{11}$$

and the output information of the hidden layer is

$$O_h(k) = f\left(I_h(k) + w^{ll} C_h(k-1)\right), \tag{12}$$

where the function $f(x)$ uses the tangsig function. The output of network is

$$y_j(k) = g\left(\sum_{h=1}^{l} w_{hj} O_h(k)\right), \tag{13}$$

where the function $g(x)$ uses the logsig function.

Since the inertial device of the strapdown inertial guided projectile starts working after the projectile is launched, the initial alignment does not begin with a static base. It is unable to collect the datum of the system in advance to train the Elman neural network. This paper uses the input and output values of the UKF to make up the pairs of datum as the learning samples. The Elman neural network is trained using the UKF estimation values and the corresponding measurement values in advance. When the errors between the network outputs and the samples are within the allowable range, this neural network can be used to accurately estimate and compensate the system to complete the initial alignment of SINS independently.

Figure 1 shows the Elman neural network diagram of initial alignment. The input nodes are the measurement variables of the system, and the output nodes are the state variables of the system. The sampling period of the system is 0.1 s.

The measurement variables $Z(k) = [\Delta L\ \ \Delta\lambda\ \ \Delta h\ \ \Delta V_E\ \ \Delta V_N\ \ \Delta V_U]^T$ are used as the inputs of the Elman neural network and weighted by calculating them to the hidden layer; the output feedbacks of the hidden layer nodes are combined with the weighted inputs of next moment to input them into the hidden layer. At this time, the outputs are weighted from the hidden layer and the system state variables $X(k) = [\delta L\ \ \delta\lambda\ \ \delta h\ \ \delta V_E\ \ \delta V_N\ \ \delta V_U\ \ \varphi_E\ \ \varphi_N\ \ \varphi_U\ \ \varepsilon_E\ \ \varepsilon_N\ \ \varepsilon_U\ \ \nabla_E\ \ \nabla_N\ \ \nabla_U]^T$ are finally obtained from the output layer.

4. Elman Neural Network Algorithm Based on GA Optimization

Although the Elman neural network is better in estimating initial values than the Kalman filter, there are still some defects when using the Elman neural network alone. Since the Elman neural network weights are updated as the way BP neural network is used, which is the gradient descent method, it is easy for them to fall into local minimum. Therefore, the GA is used to train the optimal initial weight so that the network can obtain the global optimal solution. At the same time, the GA has the characteristic of parallel search, which ensures the rapidity of the algorithm.

The GA is a global optimization method based on biological evolution process of random search. It greatly reduces the influence of the initial state through crossover and mutation operation and conducts searching in the global optimal solution rather than staying in the local optimal solution. However, the precision of the solution searched by GA alone is low. In this paper, the combination of the GA and the Elman neural network can extend the searching space of the neural network system and have the ability for global optimization. On the basis of the genetic algorithm, the solution obtained by GA is used as the initial solution of the Elman neural network.

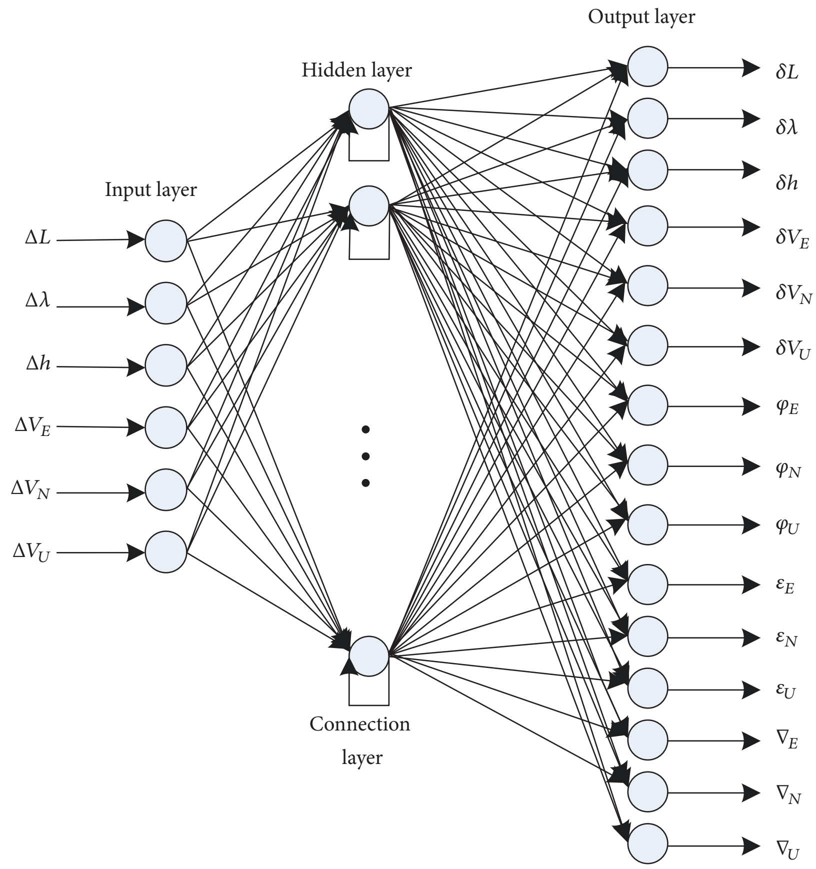


Figure 1: Elman neural network diagram of initial alignment.

The purpose of the GA-Elman network is to obtain the better initial weights and thresholds of network through the Genetic algorithm, no longer random assignment. The initial weights and thresholds of the network are represented by individuals, and every individual initialized the prediction error of neural network as the individual fitness. The method uses the operations of selection, crossover, and mutation to find the best individual, which is the optimal weight and threshold of the neural network.

Figure 2 is the flowchart of the process for GA optimizing the Elman neural network. The specific steps are as follows:

(a) Generation of the initial population: encode and arrange the number of neurons of the hidden layer and the weights and the thresholds of the network into each character string in sequence as each individual.

(b) Calculate the fitness of individuals: the training data is used to train the Elman neural network to predict the outputs of the system, which are the differences between the calculation of its genes (thresholds and weights) and the expected values.

(c) Genetic operation: record the individual with the best fitness (the smallest difference). Select the individuals with good fitness using the geometric plan ranking method; cross and vary the selected individuals, equivalent to the sexual reproduction and gene mutation of the organisms.

(d) According to the given genetic algebra, the optimal individual gene is the ultimate threshold and weight. The gene is used to initialize the neural network and then training and predicting are used to get better results.

5. Numerical Simulation

5.1. The Principle of Simulation. This numerical simulation was carried out with Matlab. The results of the initial alignment state estimation from GA-Elman network are compared with the results from using the UKF alone, which demonstrates the superiority of the GA-Elman network.

In this paper, the inputs and outputs of the UKF are used as pairs of datum for learning samples. The Elman neural network is trained by the state variables and the corresponding measurement variables obtained from the UKF in advance. When the errors between the network outputs and the samples are within the allowable range, the neural network can accurately estimate and compensate the system independently, thereby completing the initial alignment process of SINS when the Kalman filter is removed.

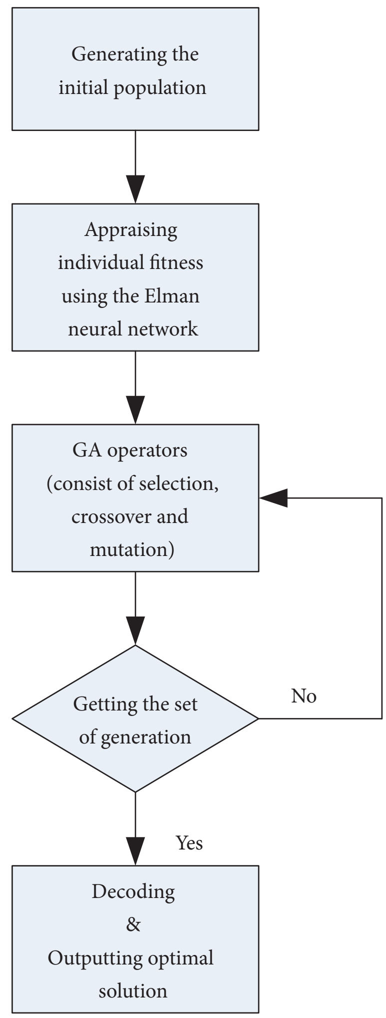


Figure 2: Flowchart of the process for GA to optimize the Elman neural network.

The principle diagram of the Elman neural network based on GA optimized for the initial fine alignment is shown in Figure 3.

When the switch is connected to state 1, the system is in the training phase of the neural network. At this time, the output state estimation e of the UKF, that is, the error of the sample expected output $\widehat{X}$ and the network output O_p, is continuously adjusted by updating the weights and thresholds. When the error e tends to the maximum allowable value, training is over.

When the neural network training is finished, the switch is connected to state 2. At this time, the neural network can replace the Kalman filter to complete the initial alignment of SINS independently.

To select the training datum, which is more suitable for dynamic system environment, the Six Degrees of Freedom (6-DOF) Ballistic Model is used to generate the trajectory of the guided projectile as in Figure 4. The state values and measurement values of the UKF on this trajectory are taken as the samples to train the neural network.

In the simulation, the number of input layer nodes of the Elman network is 6, the number of hidden layer nodes is 50, and the number of output layer nodes is 15.

The related parameters in the simulation are shown in Table 1.

5.2. Simulation Results. The fine alignment process of the initial alignment of SINS is completed independently by the trained Elman neural network based on the GA. Since the attitude matrix is corrected by the estimation of the misalignment angle in initial alignment, the simulation results of the three misalignment angles under the UKF filter and the Elman neural network are compared.

The whole simulation period is 30 s, where 10 s to 30 s is for fine alignment. The red solid line is the result of the UKF and the green solid line with circle symbol is the result of the GA-Elman.

From Figure 5, it is shown that the Elman neural network based on the GA is very accurate in state estimation, and the convergence of misalignment angle errors for the

Table 1: Nty Table 1: Related parameters.

Related parameters	Setting values
Horizontal position error of GPS (m)	5
Vertical position error (m)	10
Horizontal velocity error (m/s)	0.2
Vertical velocity error (m/s)	0.3
Measurement white noise of gyro (°/s)	0.117
Driven white noise of gyro (°/s)	0.017
Measurement white noise of accelerometer (mg)	2.061
Driven white noise of accelerometer (mg)	0.292
Correlation time (s)	3600

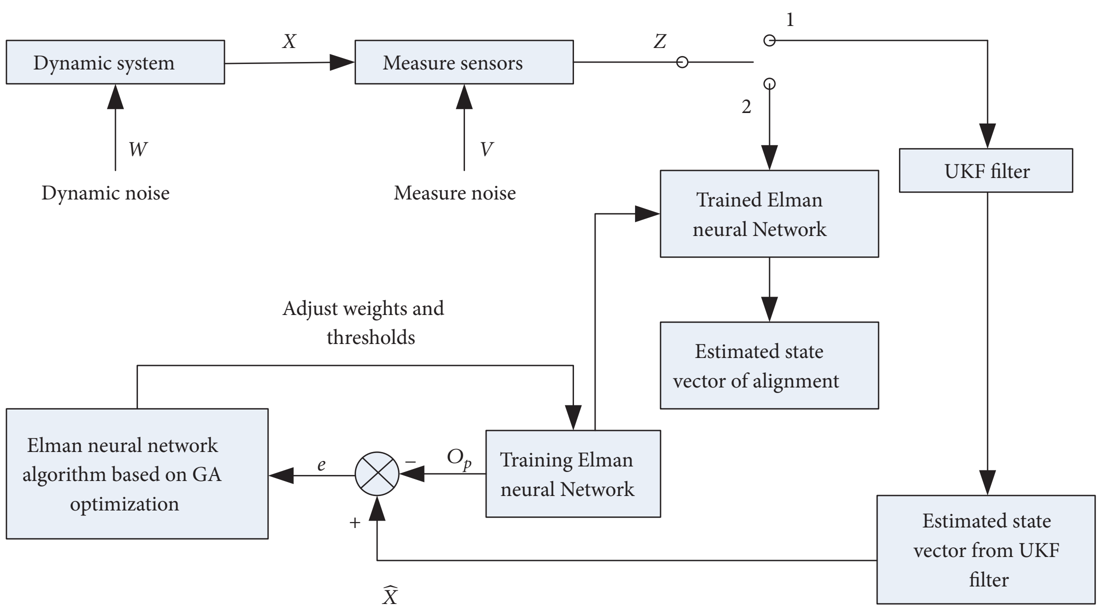


Figure 3: The principle diagram of the GA-Elman network.

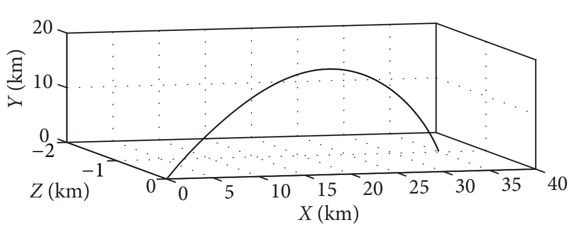
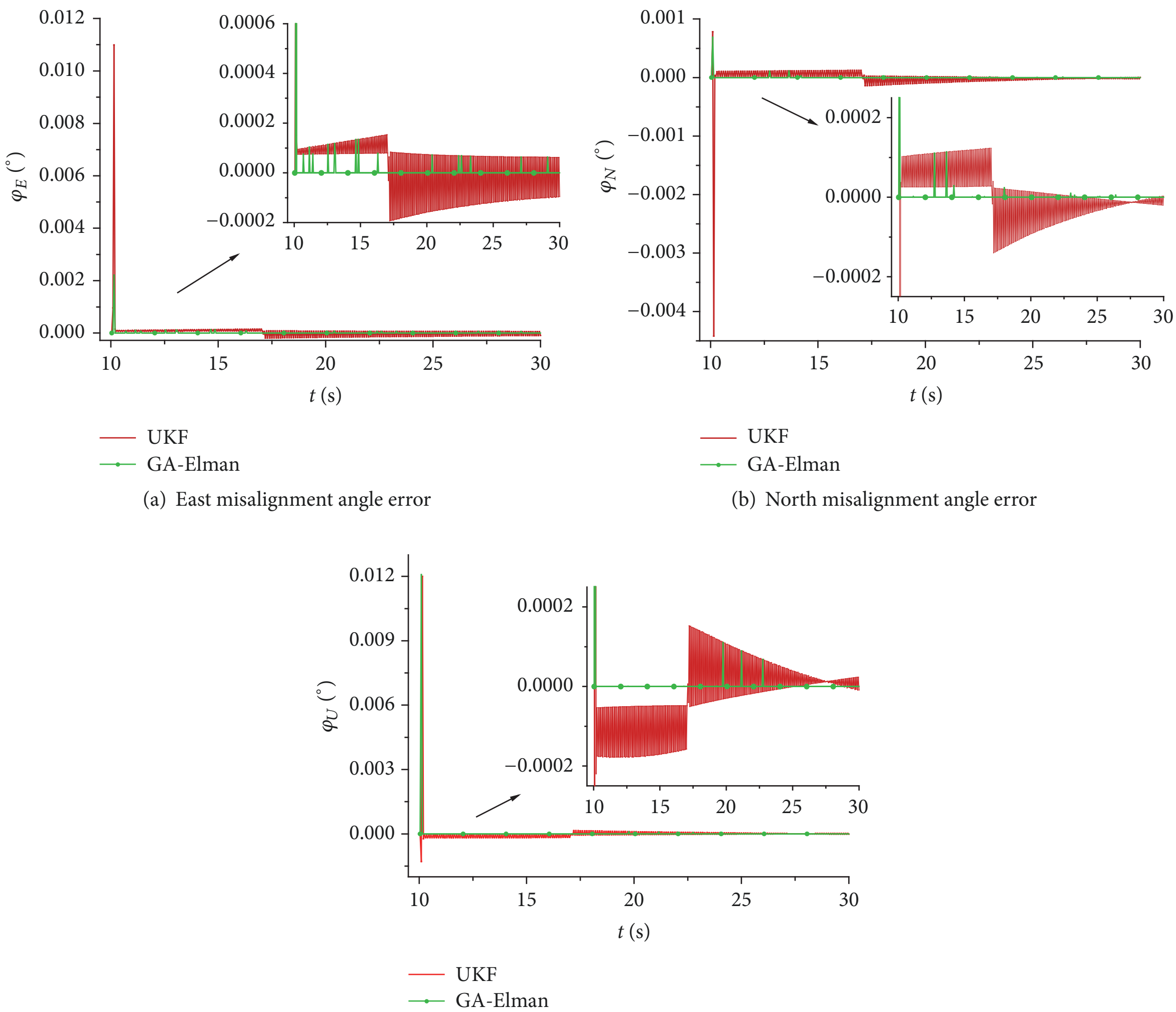


Figure 4: Trajectory of guided projectile.

GA-Elman network is better than the UKF. In other words, the application of the Elman neural network instead of the Kalman filter can not only solve the real-time problem in the Kalman filter but also satisfy the required precision. Therefore, it is feasible to replace the Kalman filter with the GA-Elman neural network. What is more, the Elman neural network is connected by a large number of simple units. The high connection makes the network insensitive to some small noise or small errors; that is to say, the network has certain robustness, so that the characteristics of the Elman network are not easily affected by the uncertain factors.

6. Summary

In this paper, an application of Elman neural network based on genetic algorithm is performed to get the initial fine alignment of the strapdown inertial navigation system for a guided projectile. This optimized Elman neural network proved its capability to solve the problems of the real-time performance and robustness of the traditional Kalman filtering algorithm in case of the initial fine alignment. The optimization of Elman neural network using genetic algorithm is more practical which solved the problem that the network easily falls into the local minimum. The simulation results illustrated that the proposed GA-Elman method is



(a) East misalignment angle error

(b) North misalignment angle error

(c) Up misalignment angle error

FIGURE 5: Estimate errors of misalignment angles.

better at estimating the misalignment angles of SINS and has the advantages of higher precision and faster calculations speed.

Data Availability

The related parameters data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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