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Application of Artificial Intelligence in Ship Integrated Navigation System

Ning Li

Department of Navigational Technology, Merchant Marine College, Shanghai Maritime University, Shanghai, P. R. China

Email address:
lining86@163.com

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Abstract: With the continuous development of navigation, modern ships put forward higher requirements for the accuracy, reliability and intelligence of navigation system. Aiming at the problems existing in the existing ship navigation system, such as insufficient navigation information fusion accuracy, increasingly important navigation safety guarantee and increasing system failure frequency, based on ship integrated navigation system, the navigation system based on artificial intelligence technology is studied. The application of artificial intelligence technology in Kalman filter fusion, navigation collision avoidance decision and intelligent fault diagnosis is deeply studied, and the navigation intelligent collision avoidance expert system is established to judge whether there will be dangerous situations such as collision, and then the decision-making gives the avoidance action plan; The navigation fault diagnosis expert system based on neural network is established to automatically diagnose the random and sudden faults such as ship equipment dysfunction or data abnormality, and the diagnosis results are given and explained. The results show that artificial intelligence technology can effectively improve the accuracy and reliability of data fusion, automatically generate collision avoidance strategies and optimization schemes when ships meet dangerous targets, and realize intelligent fault diagnosis of navigation system. It has important theoretical guiding significance for the development of new ship integrated navigation system towards higher precision, higher reliability and intelligence.

Keywords: Integrated Navigation, Fault Diagnosis, Collision Avoidance, Artificial Intelligent, Information Fusion

1. Introduction

The ship integrated navigation system combines different navigation equipment and navigation methods, and applies information fusion technology to comprehensively process the navigation information, so as to improve the data accuracy and reliability of the system. Kalman filter is commonly used to filter and fuse multi-sensor data [1], but it brings model error because it depends on the system mathematical model. Using neural network technology to compensate the error of Kalman filter estimation can improve the adaptability and estimation accuracy of Kalman filter. The problem of navigation safety has always been a major issue concerned and solved by the navigation industry. Based on the navigation collision avoidance theory and artificial intelligence technology, the research and establishment of navigation collision avoidance decision-making system is conducive to improve navigation safety and reduce the burden of seafarers. With the continuous improvement of the integration and intelligence of modern ship navigation equipment [2], it is necessary not only to provide real-time and accurate navigation information for ship control and weapon system, but also to have the ability of fault identification and state prediction. Therefore, it is of great significance to study the intelligent diagnosis system with associative memory and logical reasoning ability.

2. Ship Integrated Navigation System

With the development of ship navigation technology, the functional characteristics and performance of navigation equipment have been basically stable. The navigation system with a single sensor can not meet the requirements of data accuracy and reliability. Therefore, the ship integrated navigation system based on multi-sensor information fusion technology came into being.

And decision control terminal. Sensors generally include inertial navigation, satellite navigation, log and other equipment. As the information source of navigation system, they mainly provide ship position, heading, speed and other information. The data processing center takes the high-speed computer as the carrier, applies Kalman filter and optimization statistical theory to fuse the navigation information of each sensor, and then gives the optimal solution of each navigation parameter. Decision control terminal is the application terminal of navigation parameters, which mainly includes system equipment such as information display, control and command, weapon operation and so on. The integrated navigation system based on multi-sensor information fusion not only effectively improves the accuracy and reliability of navigation data, but also lays an important foundation for intelligent applications such as ship navigation collision avoidance, fault diagnosis and comprehensive decision-making.

3. Artificial Intelligence Technology

As a branch of computer science, artificial intelligence is committed to the automation of intelligent behavior [3]. The research in the field of artificial intelligence mainly includes three aspects: neural network, fuzzy logic and expert system.

Artificial neural network is an information processing system that can simplify and simulate the structure and function of human brain, establish the nonlinear mapping relationship between system input and output through the wide interconnection of neurons and certain learning mechanism, and then respond dynamically according to external information [4]. The process of establishing the system neural network model is shown in Figure 1. Firstly, the demand background and functional model of the system are analyzed, and the neural network structure is set; Then the neural network model is trained based on a large number of sample data to make the model closer to the actual work of the system; Finally, after the evaluation and test weights meet the requirements, the networked dynamic relationship between system input and output is established; The neural network model continues to learn and optimize in the working process [5].

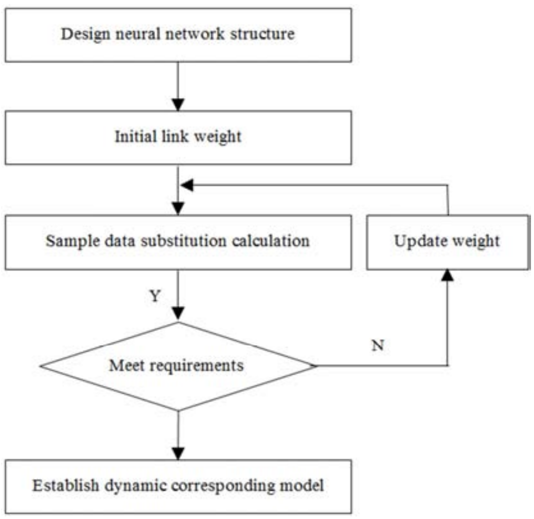

Figure 1. *The learning process of neural networks.*

Because objective things are becoming more and more complex, some fuzzy languages are often used to summarize some attributes of things, and uncertain reasoning is used to describe the relationship between fuzzy things. Fuzzy logic reasoning is a common uncertain reasoning method, and its reasoning mechanism includes the following steps: 1) the uncertain elements in fuzzy propositions are expressed in the form of qualitative values to form fuzzy sets, and the membership function is deduced according to the relationship between fuzzy elements and the sum of fuzzy sets; 2) Experts make fuzzy rules based on the fuzzy relationship in the problem, and use fuzzy rules to establish the mathematical model of operating fuzzy sets; 3) The expert knowledge base is constructed according to a certain mathematical expression of fuzzy set, membership function, fuzzy rules and fuzzy set operation model; 4) Based on the fuzzy logic relationship in expert knowledge base, the mathematical relationship between fuzzy proposition and inference is established.

Expert system is a program system that uses expert knowledge group to build a knowledge base, searches and matches in the knowledge base according to the problem characteristics, and solves specific problems by reasoning. The composition structure of the expert system is shown in Figure 2. Firstly, based on expert knowledge and experience, the system knowledge base is created according to a certain form of data storage; The reasoning module searches for matching in the knowledge base according to the characteristics of the problem information, continues to ask for supplementary information from the user according to the needs, and gives the problem solution after reasoning and analysis. Finally, users can seek explanation from the expert system according to their understanding needs, and the expert knowledge base automatically supplements and updates the system knowledge according to the problem-solving situation.

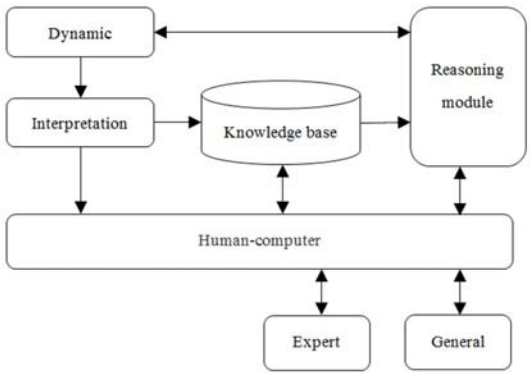

Figure 2. *General structure of an expert system.*

4. Neural Network Aided Navigation Information Fusion

4.1. Kalman Filter Algorithm

Kalman filter is a linear minimum variance estimation proposed by Kalman. The expression of system state equation and measurement equation of discrete Kalman filter algorithm is [4]:

$$\begin{cases} X_k = \phi_{k,k-1}X_{k-1} + \Gamma_{k,k-1}W_{k-1} \\ Z_k = H_k X_k + V_k \end{cases} \quad (1)$$

Where: X_k is the estimation sequence of system results; Z_k is the observation sequence of the system result, and W_k is the noise sequence of the parameter transmission process in the system; V_k is the observation noise sequence of the system result; W_k and V_k are independent of each other. $\phi_{k,k-1}$ is the system state transformation matrix, $\Gamma_{k,k-1}$ is the external noise input transformation matrix, H_k is the measurement transformation matrix, and the following relationship is satisfied:

$$\begin{cases} E[W_k] = 0, E[W_k W_j^T] = Q_k \delta_{kj} \\ E[V_k] = 0, E[V_k V_j^T] = R_k \delta_{kj} \\ E[W_k V_j^T] = 0 \end{cases} \quad (2)$$

Where: R_k is the variance matrix of system measurement noise sequence; Q_k is the variance matrix of system process noise sequence; δ_{kj} is Dirac $-\delta$ function and satisfies $\delta_{kj} = \begin{cases} 1, (k=j) \\ 0, (k \neq j) \end{cases}$. The discrete Kalman filter algorithm in equation 1 is calculated and deduced to obtain:

$$\begin{cases} \vec{X}_k = \vec{X}_{k,k-1} + K_k[Z_k - H_k \vec{X}_{k,k-1}] \\ K_k = P_{k,k-1}H_k^T[H_k P_{k,k-1} H_k^T + R_k]^{-1} = P_k H_k^T R_k{}^{-1} \end{cases} \quad (3)$$

Where: K_k is the Kalman filter gain matrix. If the gain is large, it means that the weight of the prediction result of the calculation system focuses on the observed value, otherwise it means that it focuses on the estimated value. Assuming that the observed value at time k is Z_k, if the initial values $\vec{X}_0$ and P_0 are known, the state estimation result $\vec{X}_k(k-1,2\ldots)$ at time k can be obtained by recursion.

4.2. Application of Federated Kalman Filter in Integrated Navigation

Based on the combination of multiple sub Kalman filters into federated Kalman filter, multiple data fusion can be realized and the optimal results can be obtained. Taking two sub filters (N=2) as an example, the data fusion process is explained. Let $\vec{X}_1$ and $\vec{X}_2$ be the state estimation of the two sub filters, and the corresponding estimation error variances are P_1 and P_2, then the fused state estimation $\vec{X}_g$ is [6]:

$$\vec{X}_g = [P_1{}^{-1} + P_2{}^{-1}]^{-1}(P_1{}^{-1}\vec{X}_1 + P_2{}^{-1}\vec{X}_2) \quad (4)$$

It can be seen from equation (4) that if the estimation accuracy of $\vec{X}_1$ is low, its contribution $P_1{}^{-1}\vec{X}_1$ to global estimation is relatively small, and its information fusion concept is consistent with Kalman filter. The above theory is also applicable to the state fusion estimation of N sub filters.

In the integrated navigation system, inertial navigation system is generally used as a reference common system, that is, its output value is used as the system observation value $\vec{Z}_i$. The system main filter applies the data fusion theory in equation (4) to fuse the system observation value $\vec{Z}_i$, the observation error variance P_{1i}, the estimation value $\vec{X}_i$ of the measurement sensor and the estimation error variance P_{2i} of the corresponding sub filter, so as to obtain the global optimal estimation value $\vec{X}_g$ of the test quantity. The estimation error variance P_g of the system is returned to each sub filter to optimize the parameters of the system state model.

4.3. Improved Kalman Filter Algorithm Based on Neural Network

The system model error caused by environmental noise reduces the accuracy and stability of data fusion. According to the input-output relationship of the system and the dynamic influence process of the environment, an adaptive neural network model is established to realize the dynamic compensation of the fusion result of the Kalman filter, so as to effectively reduce the influence of the model error on the filtering accuracy [7].

The basic principle of neural network assisted Kalman filter is shown in Figure 3: 1) analyze the system model and input and output samples, and establish the neural network structure and initial parameters; 2) The output X_g of the federated Kalman filter is taken as the initial estimation of the system, and the $\vec{X}_k$ calculated by the neural network is regarded as the error compensation estimation; 3) The neural network is trained by the difference between the calculated $\vec{X}_k$ and the expected output $\vec{X}_k$ to optimize the model parameters; 4) The neural network model outputs the correction value P_g, compensates the error of the initial estimation X_g, and takes the compensated $\vec{X}_g$ as the final estimation result of the system.

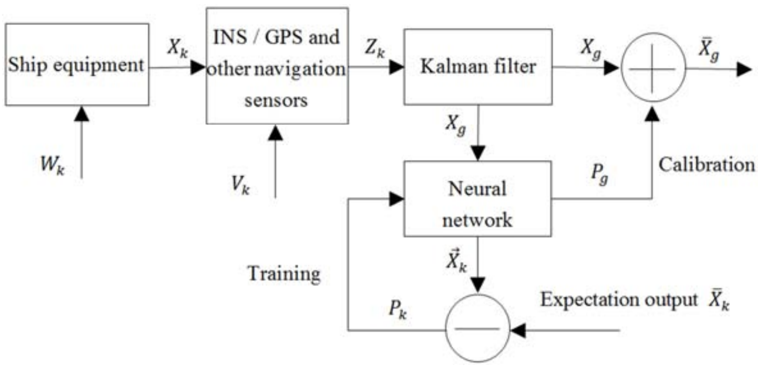

Figure 3. *Block diagram of neural network-assisted Kalman filtering.*

5. Marine Intelligent Collision Avoidance Expert System

5.1. System Scheme Design

The navigation intelligent collision avoidance expert system uses the detection sensor to detect the dangerous target, receives the navigation information directly sent by the command center and other ships through the wireless network, calculates and infers based on the knowledge cases in the navigation expert knowledge base, judges whether there will be collision and other dangerous situations, and then makes a decision to give a collision avoidance action plan [8].

The design scheme of Marine Intelligent Collision Avoidance Expert system is shown in Figure 4. In the stage of judging the collision risk, the system calculates the collision risk based on the collision risk model according to the target motion state and marine environment information; In the stage of judging the collision risk situation, the system matches and identifies the current collision situation according to the relative position and navigation information of the two ships; In the ship avoidance decision-making stage, the system makes comprehensive reasoning based on collision risk and collision situation and expert knowledge and experience. In this process, the system can obtain supplementary information or transmit interpretation information through human-computer interface, and finally determine the collision avoidance strategy and action plan; In the knowledge base update stage, the system improves the content of the knowledge base through a certain information description mechanism based on the newly generated collision cases and processing experience.

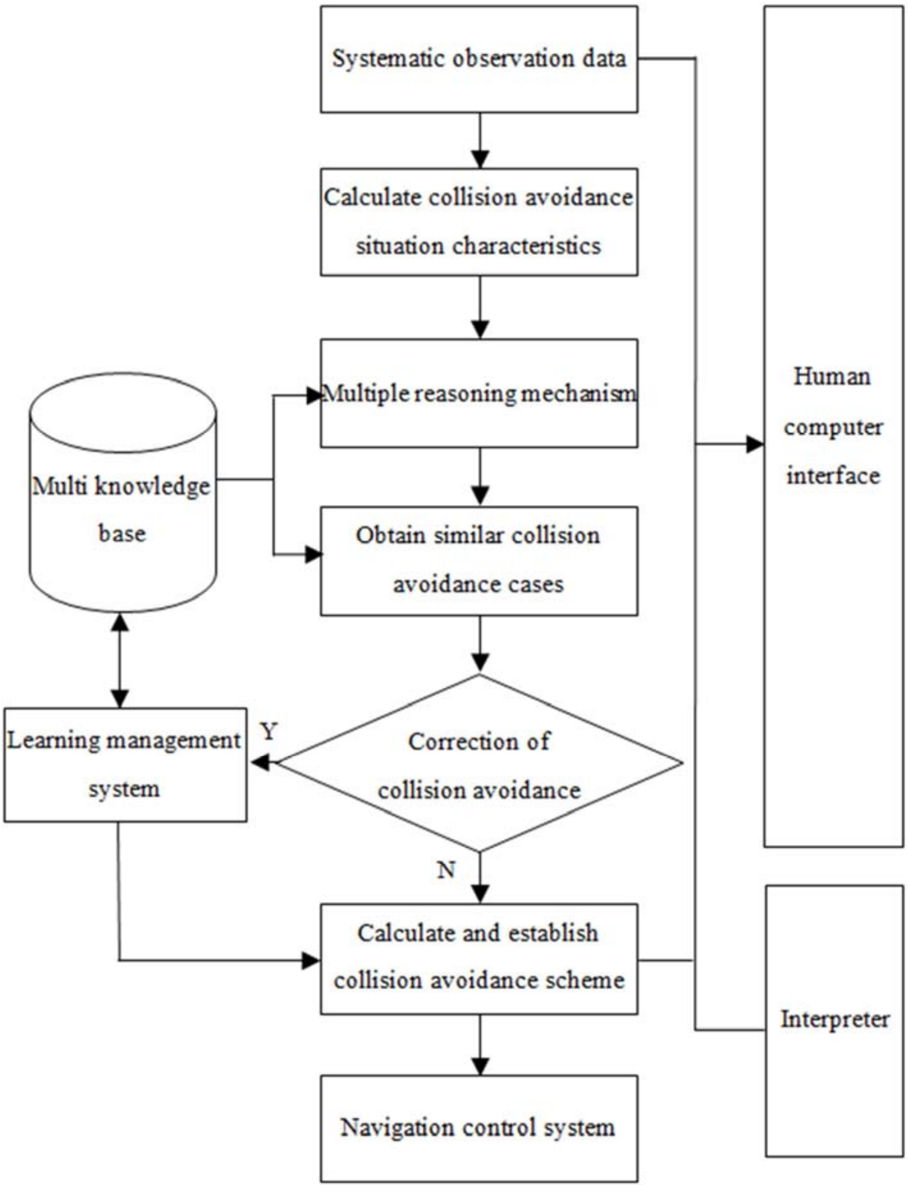

Figure 4. *Design scheme of collision avoidance system for marine experts.*

5.2. Establishing System Model

5.2.1. Collision Risk Model Based on Fuzzy Principle

The collision risk model is established with DCPA (D, minimum encounter distance), TCPA (T, minimum encounter time) and range (R, distance between ship and target) as the main factors, as shown in the following formula [9]:

$$\begin{cases} d_1 = (K_1 DLA + T \cdot V_R \cdot F_1) \cdot F_2 \cdot F_3 \\ F_1 = \begin{cases} \frac{360° - DE}{360°} DE \leq 180° \\ \frac{DE}{360°} DE > 180° \end{cases} \\ DE = \begin{cases} Target\ current\ azimuth\ DCPA \leq 0.5\ nm \\ azimuth\ of\ target\ CPA\ point\ DCPA > 0.5\ nm \end{cases} \\ d_2 = K_2 \cdot d_1 \\ \mu_A = a_D \cdot \mu_{AD}(D) + a_T \cdot \mu_{AT}(T) + a_R \cdot \mu_{AR}(R) \end{cases} \tag{5}$$

Where: d_1 and d_2 are the measurement distance of hazard judgment; DLA is the distance between ships when collision avoidance action is taken at the latest; K_1 is the encounter type coefficient; K_2 is the ship state coefficient; T_0 is the time required for the ship to turn 90°; V_R is the relative speed of the target ship; F_1 reflects the target azimuth factor; F_2 represents visibility factor; F_3 reflects the current water area. μ_A is the comprehensive collision risk of the ship; $\mu_{AD}(D)$, $\mu_{AT}(T)$ and $\mu_{AR}(R)$ are the collision risk of encounter distance, encounter time and target distance respectively; a_D, a_T and a_R are influence weights; DLA, T, K_1, K_2, a_D, a_T and a_R are historical navigation conditions and empirical data, which are obtained by fuzzy logic reasoning [10].

The ship judges the collision risk between the ship and the dangerous target based on the minimum encounter distance and measurement distance. When $DCPA < d_1$, it is considered that the target has constituted a collision risk; When $DCPA > d_2$, it is considered that there is no collision risk; When $d_1 <$ DCPA $< d_2$, it is considered that the ship has a certain collision risk, and its risk degree is calculated by the collision risk model.

5.2.2. Ship Encounter Situation Reasoning Model Based on Neural Network

During the meeting between the ship and the target ship, according to the navigation collision avoidance rules, the meeting situation is generally divided into: opposite meeting (port, starboard), small angle intersection (port, starboard), large angle intersection port, starboard), overtaking and being chased, etc. each meeting situation includes a variety of meeting states. According to the previous experience of situation discrimination during navigation, the course crossing angle C and the target ship side angle Q are usually used as the main discrimination basis.

The basic structure of ship encounter situation reasoning model based on neural network is shown in Figure 5. Firstly, the network structure of the reasoning model is established. The subnets NN1 and NN2 are used for the information input of side angle Q and course crossing angle C, V_r is the system external error, and NN3 is used for fuzzy reasoning of encounter situation; The expert conclusions and navigation experience are described in a certain mathematical language, the weight parameters of the network model are determined, and they are constantly revised in the work. Finally, the model infers according to the information of chord angle Q and cross angle C, and obtains the encounter situation results.

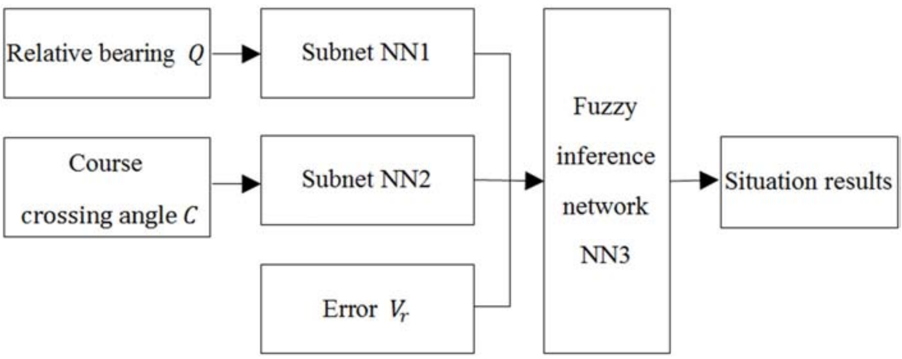

Figure 5. *Situational Network Reasoning Model.*

5.2.3. Ship Avoidance Decision Model Based on Fuzzy Decision

When two ships pose a collision risk, one or both of the two ships shall take avoidance action. Ships adopt different avoidance strategies and actions according to collision risk, encounter situation, motion state, marine environment and other factors. In the navigation rules, the avoidance action encountered by the two ships is divided into four stages: avoidance action, collision risk, urgent situation and urgent danger [11]. Therefore, the decision-making problem of ship collision avoidance is transformed into the problem of judging the stage of avoidance action. Taking the ship collision risk, encounter situation, motion state and external environment as the four fuzzy factors of the model, the collision avoidance rule base is established by comprehensively applying expert theory and historical collision avoidance cases [12]. Through reasoning analysis and matching algorithm, the nonlinear logical relationship between the current dangerous situation and collision avoidance action strategy is obtained. The current encounter information is quantified, and the matching reasoning is carried out according to the collision avoidance rules and neural network to determine the current collision avoidance action stage, and the collision avoidance action scheme is determined according to the stage requirements [13].

6. Navigation Fault Diagnosis Expert System Based on Neural Network

6.1. System Composition Structure

Fault diagnosis expert system is an intelligent diagnosis system based on ship navigation and troubleshooting experience, which uses the logical reasoning ability of neural network to solve the problems of random and sudden faults [12]. The principle of fault diagnosis expert system is shown in Figure 6. Firstly, based on expert data and troubleshooting cases, the connection weight of neural network is calculated and the knowledge base is built; The expert system automatically diagnoses the ship equipment. When the equipment is dysfunctional or the data is abnormal, it infers the fault cause and predicts its development trend; When the user sends a diagnosis request to the diagnosis system, the system performs case matching and reasoning according to the requested symptom information, and asks for supplementary information from the user according to needs; Finally, the diagnostic results are obtained and explained. If new diagnosis experience is obtained in troubleshooting, the system will automatically supplement the knowledge base.

6.2. Build Knowledge Base

Knowledge base is the key to establish fault diagnosis expert system [15], and its quantity and quality of knowledge determine the technical level of expert system. The solution process of fault problem is the process of reasoning and interpretation of fault characteristic information based on knowledge cases in knowledge base by simulating human expert thinking. The establishment steps are as follows: 1) analyze the fault knowledge structure of the diagnosis object and determine the neural network model; 2) Select fault diagnosis samples to train the neural network, calculate the connection weights between input layer and hidden layer, hidden layer and output layer, and establish the mathematical reasoning relationship between fault symptoms and fault causes; 3) Store connection weights and establish a knowledge base.

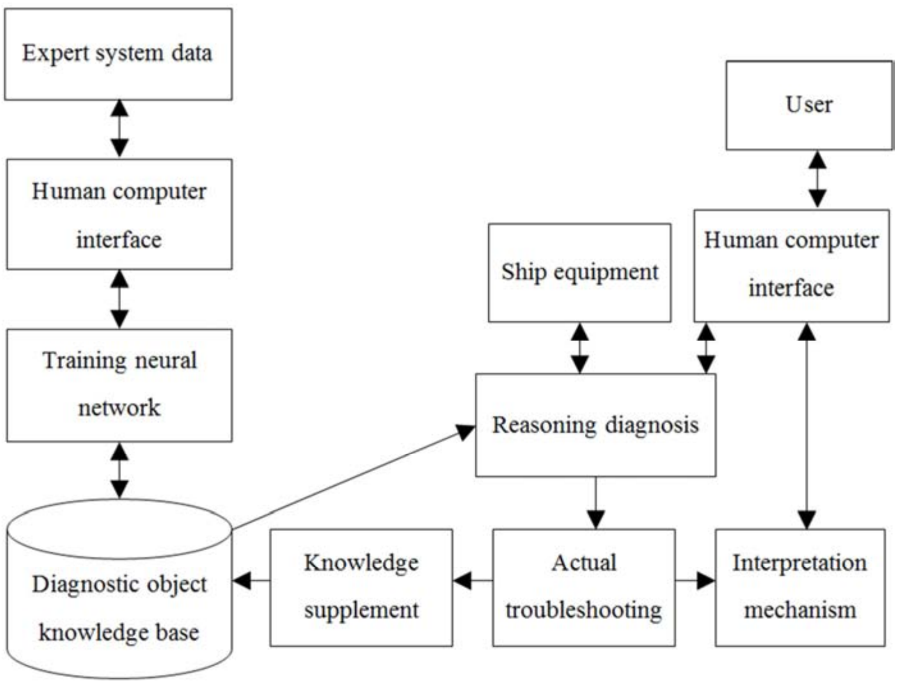

Figure 6. *Structure chart of fault diagnosis expert system.*

6.3. Neural Network Design of System

The design of neural network for fault detection is shown in Figure 7. Its structure can be divided into three parts: sample input layer, hidden layer and result output layer. INS, GPS, log and other sensors constitute the system input layer, and each sensor information variable corresponds to a node of the input layer; The hidden layer is composed of neurons. The number of hidden layers and neurons are determined based on the input-output relationship, learning speed and reasoning ability; The output layer receives the numerical results of fault diagnosis calculated by the hidden layer, performs matching reasoning based on the expert knowledge base, and gives the final diagnosis results. The key to the design of neural network is to calculate the connection weight between networks. Firstly, the connection weights are preset according to the system network model; Then, the input sample information is calculated along the specific neuron path, and the calculation results are transmitted to the output layer; If the calculated output value is inconsistent with the expected value of empirical theory, the difference between the two is propagated back along the original connection channel, and the connection weight is modified until the expected target is met.

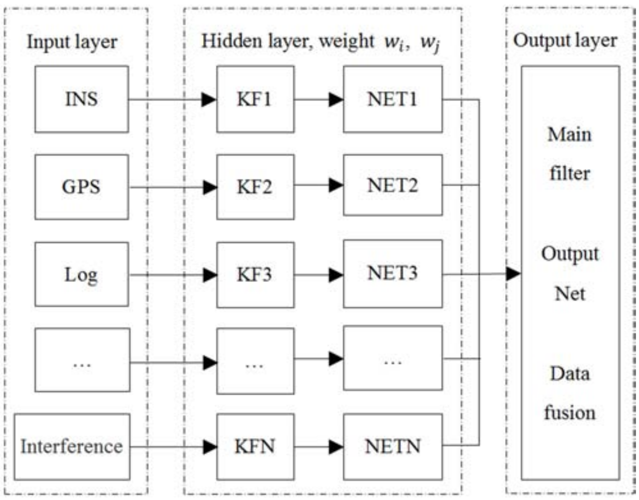

Figure 7. *Neural network design for fault detection.*

6.4. Reasoning Mechanism of Fault Diagnosis

According to the mathematical logic relationship in the knowledge base, the fault diagnosis expert system matches and infers the fault symptom information based on the neural network model, and finally obtains the diagnosis result. The system reasoning mechanism includes forward reasoning, reverse reasoning and hybrid reasoning. Forward reasoning is the known fault symptom information, and the fault diagnosis results are obtained by neural network calculation and knowledge base matching; Reverse reasoning is to assume a fault diagnosis result according to the fault symptoms, and then calculate the diagnosis result by reverse neural network, calculate and verify whether the calculation results are consistent with the fault symptoms; Hybrid bi-directional reasoning is to know some fault symptom information, propose a possible fault according to the symptom information, and then verify whether the hypothesis is true. If it is true, the diagnosis ends. Otherwise, make a new hypothesis based on the diagnosis to continue the verification.

7. Conclusion

In the process of navigation information fusion using Kalman filter, the dynamic error compensation of the estimation results according to the neural network model can effectively improve the accuracy and reliability of data fusion. Based on expert system and fuzzy neural network, the collision risk calculation, encounter situation classification and avoidance decision model of ships are established, and the collision avoidance strategy and optimization scheme when ships meet with dangerous targets are given. Using the reasoning ability and matching algorithm of expert neural network, the corresponding relationship between system fault symptoms and diagnosis results is established, and then the intelligent diagnosis of navigation system fault is realized. With the continuous development of emerging technologies such as machine learning and image processing, the ship integrated navigation system with higher accuracy, reliability and intelligence will usher in greater application prospects.

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