Study on NN-based Intelligent Exploring Module of the Fire-sprinkling System

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Abstract. The intelligent exploring module is precondition of the Fire-sprinkling System effective-working. The NN-based intelligent exploring module explores the condition of the cabin and fuses all the explored information, including temperature, flame, smog, pressure. The method is effective to improve the performance of the system.

1. Introduction

The ammunition depot, fuel tank and other special cabins on warships are high-risk flammable and explosive places. No matter which special cabin fire or explosion accident will directly endanger the lives of the crew and the safety of the carrier. The consequences will be unimaginable. Therefore, when a fire or deflagration accident occurs in a special cabin, how to take appropriate fire suppression and explosion suppression measures for different types of special cabins to quickly and effectively suppress the spread of fire and minimize the loss has always been an urgent need of warships. The major technical problem will be solved by the fire-sprinkling system.

Cabin fire can be divided into two categories: one is slow fire, such as fire caused by inflammable substances in storehouse or bullet in adjacent cabin. Its response speed to fire control system is low, and the current shipboard fire control system can meet the requirements. The other is rapid ignition, such as accidental ignition of booster ammunition in cabin, it may trigger explosion in a very short time, give us a very short time from discovering accidental ignition to taking measures to suppress explosion. The current fire control system can not meet the rapid requirement.

Based on the analysis of the function and performance requirements of the fire-sprinkling system, combined with modern detection technology and information processing technology, the paper designs a new Intelligent exploring module to meet the requirements of the cabin accidental ignition detection. The new Intelligent exploring module can improves the speed, fault tolerance and accuracy of the system.

2. Design of the Intelligent Exploring Module

At present, the conventional fire extinguishing system in ship fire fighting is adopted in our country. It has temperature detectors and smoke detectors. The detectors can monitor two kinds of information, temperature and smoke. But they are independent and no considered comprehensively. They are a single point and single information detection, and their false alarm rate and reaction speed still have a relatively large space to improve.
Aiming at the special object of cabin fire, the paper adopts two-level fusion processing method. The intelligent exploring module is a primary data fusion processing unit, include integrates time. It can synthetically analyze and fuse many kinds of information collected in this area, such as temperature, pressure, smoke, flame and so on, and output the data fusion results to the host computer. Secondary data fusion processing unit uses multiple Intelligent exploring modules distributed in space to form detection system, not only enlarges the scope of detection area, but also uses multiple detection modules to fuse detection information, it can improve the accuracy and rapidity of information abstraction. The system data processing block diagram is shown in Figure 1.

![Figure 1. The system data processing block diagram](image1)

The intelligent exploring module includes temperature detection, temperature gradient detection, pressure detection, pressure gradient detection, fire detection, smoke detection, or one or several combinations (the different cabins can take the corresponding detection combination). Its hardware circuit mainly includes the following parts: detector, signal processing unit, MCU, communication interface unit. The specific block diagram is shown in Figure 2.

![Figure 2. The specific block diagram](image2)

The core part of hardware circuit of Intelligent exploring module is MCU. Each detector inputs the information measured by every signal processing unit of detector into the single chip computer. The MCU uses data fusion technology to analyze and process all the data, and gets the current state. The MCU can transmite data to the upper computer through the communication interface unit and the bus. In order to realize external communication and standardization of interface, the system will be configured the standard interface bus. The CAN bus is chosen as the data communication mode. It adopts many new technologies and unique design. Compared with the general communication bus, the CAN bus is outstanding reliability, real-time and flexibility.

3. Neural Network

Fire detection is a non-structural problem. The traditional mathematical modeling method is difficult to complete. It requires signal processing algorithm to adapt to the changes of various environments and automatically adjust parameters to achieve both the rapid fire detection and the low false alarm rate. No matter what kind of fixed algorithm program is used, it is difficult to meet the requirements. The Neural network can avoid the direct analysis of the system internal characteristics, can be the
system as a black box. The Neural network simulates the actual system by simulating the external characteristics of the system, and adapts to different environmental requirements through its self-learning performance.

For the data fusion of multi-sensor information in cabin, the Intelligent exploring module adopts the neural network. It is not a simple combination of single parameter fire detectors, but it is a multi-sensor detection information. The module is processed synchronously by using intelligent algorithm according to different environmental factors and different fire parameters.

3.1. Network Model Design
The intelligent exploring module will use BP neural network, its model is 7-4-1, the specific structure is shown in Figure 3.

![Network Model Diagram](image)

First Layer  Second Layer  Third Layer
Figure 3. the basic structure of the Network Model

The first layer is the detector output signal processed layer by the signal processing unit. The smoke signal, fire signal, temperature signal and pressure signal are derived from the output of the corresponding detector, and the temperature gradient and pressure gradient are calculated based on the input of temperature and pressure and their historical information, they are recorded as $x_1 \sim x_6$. The physical quantities of input nodes are different. To prevent the small values from being flooded by the large values, and to prevent the network correction process from slowing down due to the large differences, the paper normalize the input signals.

Because the formation of fire is a certain process, the single threshold setting alarm will cause delayed alarm (too high threshold), or false alarm (too low threshold). So the formation of fire must be analyzed continuously. At the same time, in order to effectively prevent false alarm caused by interference signals, this paper introduces feedback into the system. The feedbacks of the current output trend back to the input of the reasoning system.

The second layer is the hidden layer, it has four nodes. The output of each node is as follows:

$$ y_j = f\left(\sum V_{ij}x_i\right) $$

Where $i = 7, j = 4$, the $f$-function is Sigmoid function.

$$ f(x) = \frac{1}{1 + e^{-x}} $$

The third layer is the network output layer.
3.2. Network Algorithms

In order to overcome the shortcomings of slow convergence speed and easy to fall into local minimum of standard BP algorithm, BP network algorithm combining adaptive learning rate and additional momentum method is adopted in Intelligent exploring module.

The combination of additional momentum method and adaptive learning rate:

\[
W(k + 1) = W(k) - \eta(k) \left(1 - \alpha \right) \frac{\partial E}{\partial W(k)} + \alpha D - \frac{\partial E}{\partial W(k - 1)}
\]  

(4)

\[
\eta(k) = 2^k \eta(k - 1)
\]  

(5)

\[
\lambda = \text{sign} \left[ \frac{\partial E}{\partial W(k)} \frac{\partial E}{\partial W(k - 1)} \right]
\]  

(6)

\[
E = \frac{1}{2} \sum_{k=1}^{r} \left( \hat{z}_k - z_k \right)^2
\]  

(7)

Thus, \( r \) is the sample number, \( E \) is the network error, \( \hat{z}_k \) and \( z_k \) are the expected output and the actual output, \( W(k) \) is the weight vector, \( \eta(k) \) is the learning rate in the \( k \) time, \( \eta(k - 1) \) is the learning rate in the \( k - 1 \) time, \( \eta > 0 \), \( \alpha \) is the momentum factor, \( 0 < \alpha < 1 \). The momentum term added by the additional momentum method is essentially equivalent to the damping term. It reduces the oscillation trend of the learning process, reduces the sensitivity of the network to local details of the error surface, and effectively restrains the network from trapping in the local minimum. The adaptive learning rate adjusts the step size according to the direction of function gradient change. When the gradient direction of two iterations is the same, the step size will be doubled. When the gradient direction of two successive iterations is opposite, the step size will be reduced by half. The combination of adaptive learning rate and additional momentum method can effectively accelerate learning speed and improve convergence.

4. System Simulation

4.1. Network Training

The neural network module in MATLAB is used for simulation training. The selection of training sample set is mainly based on the data obtained in the range laboratory and related data. The training samples will be need, include some combinations, but should cover all input fields. When defining the relationship between input and output, important samples should be taken into account. The basic principles of sample selection are as follows: corresponding to the region where the maximum and minimum sample points of input and output are located; the region where the output change rate is larger has larger sample density, while the region where the output change rate is smaller has smaller sample density.

Selecting 20 representative groups of data for simulation training. The error \( E < 0.001 \) is the total error of system. Fig. 4 is the simulation error curve. It can be seen from the figure that after 5 training sessions, the system meets the error requirements.
Figure 4. the simulation curve of the error

4.2. Performance Improvement

By inputting some interfering data into the Intelligent exploring module trained by the network and observing its output, comparing with the original system, it is found that the Intelligent exploring module based on the neural network has the following advantages:

4.2.1. Fault-tolerance

To the original system, the single detector error or failure is very likely to cause false alarm or missed alarm. The Intelligent exploring module can still work normally, and has little impact on the output of the whole module. The intelligent exploring module is a comprehensive consideration of all input information, does not depend on any single information, can more truly reflect the current state of the environment. The false alarm rate is very low. In a certain state, the other detection information remains unchanged, the temperature suddenly increases from 20℃ to 100℃ and the output of Intelligent exploring module rises from 13.2% to 14.5%, it is still far below the alarm threshold and will not be misreported. In the same case, a single detection system will be misreported.

4.2.2. Complementarity

The detectors provide the common reaction of the objects and the characteristic response related to the detectors themselves. Therefore, the use of neural networks can complement the data of different detectors, obtain more data in less time, improve the utilization rate of data and the recognition efficiency of the system, reduce the uncertainty of the system understanding, improve the accuracy and reliability of the system. It improve the accuracy and reliability of the system. The intelligent exploring module fully considers the complementarity of many information when fire occurs. When most parameters are close to their threshold, but any single parameter does not reach the alarm threshold, it can give an early warning according to the changing trend of multiple parameters.

4.2.3. Rapidity

In order to prevent false alarm caused by interference, the single detector of the original system adopts the method of prolonging the filtering time. In order to achieve the filtering effect, the time constant must choose a larger value. The intelligent exploring module has a certain filtering effect. By introducing feedback at the input of the neural network, referring to historical information, continuous analysis, and referring to the input information of other detectors. It can significantly reduce the filtering time and improve the rapidity. After testing, the detection time of the system is only 40% of that of the original single detector.
5. Conclusion
Based on the analysis of the performance requirements of the fire-sprinkling system, and combined with modern detection technology and information processing technology, this paper designs an Intelligent exploring module for the detection requirements of cabin accidental ignition. It uses neural network to fuse multi-information such as temperature, pressure, smoke, fire and so on. It makes full use of the complementarity of multi-information and improves the accuracy and fault tolerance of the system. In the case of single detector error or failure, the module can still work normally; it improves the speed and reliability of the system, reduces the detection time constant to 40% of the original; further reduces the false alarm rate, so that the Intelligent exploring module meets the requirements of cabin detection. At the same time, the improved BP algorithm is used to speed up the network training.

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