Design of an Intelligent Alarm System Based on Multi-sensor Data Fusion

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Abstract: The fire alarm system plays a very important role in life, but the system has problems such as false alarms and false alarms. Therefore, this paper proposes the application of fire detection based on GA-BP neural network. Firstly, the algorithm takes temperature, smoke concentration and CO concentration as the input of BP neural network, and the output is whether there is fire or not. Secondly, it combines the characteristics of genetic algorithm with strong global search ability and strong robustness. The algorithm has achieved 100% correct classification on the test set through simulation experiments. At the same time, the absolute error of the sample prediction is only 0.006, which proves that it has strong robustness, reliability and generalization ability. Finally, the model was transplanted to STM32 to prove its feasibility. This method provides a new method for intelligent identification of fire signals for early warning of fires and accurate identification of non-fire signals.

1. Introduction
With the increasing use of fire and electricity in modern times, the frequency of fires is getting higher and higher. In the early stage of a fire, the surrounding environmental conditions (such as temperature and smoke) will change, and they are related to each other. The traditional fire detection device only detects the data of a single sensor to determine whether there is a fire. For example, the smoke sensor will only alarm when the smoke concentration reaches the set value, and ignore the influence of factors such as temperature and CO concentration. In more complex situations, missing alarm and error alarm are prone to occur [1-4].

The simple circuit connection of multi-sensors is susceptible to various interferences, and many experts and scholars have conducted research on fire prediction using neural networks. Eric Wai Ming Lee used the incremental adaptive neural network model of online noise data regression to study the cabin fire [5]. Caixia Cheng and Fuchun Sun used artificial neural networks to monitor fire sensor signals, reducing the missing and false alarm rate [6]. Pu Li and Wangda Zhao proposed an algorithm based on YOLO v3 to detect fires, improving the accuracy and speed of detection[7].Khan Muhammad and Jamil Ahmad propose an early fire detection framework using fine-tuned convolutional neural networks[8].L. Yang and C. W. Dawson proposed the use of logistic regression models, neural network models and genetic algorithms to predict fires, of which genetic algorithms are better[9].Faozui Derbel proposed two algorithms for multi-sensor fusion to solve the problem of poor single sensor performance. Among them, the neural network algorithm is better [10]. Fire is one of the
major disasters in the world. The fire detection system should detect fires in various environments (for example, buildings, forests, and rural areas) in the shortest time to reduce economic losses and man-made disasters. In fact, fire sensors are complementary to traditional point sensors (for example, smoke and heat detectors), which can provide people with early warning of fire occurrence [11].

Although BP neural network can predict fire to a certain extent, it has the problems of easy to fall into local minimum and slow convergence speed. To avoid the local minimum effect caused by the traditional NN-based model, genetic algorithm (GA) is utilized to optimize the initial weights of neural networks [12]. This article uses multi-sensor fusion, genetic algorithm and neural network to determine the contribution of each sensor in fire recognition, so as to achieve the effect of greatly reducing the false alarm rate, the accuracy has been greatly improved, and the performance has been enhanced.

2. Fire detection and alarm principle

2.1. Working principle of fire sensor

At present, there are two types of temperature sensor: thermocouple and thermistor. The thermocouple is composed of two different metal wires (metal A and metal B) connected at one end. When the thermocouple is heated at one end, there is a potential difference in the thermocouple circuit. The measured potential difference can be used to calculate the temperature. The thermistor type uses semiconductor materials, which are mostly negative temperature coefficients, that is, the resistance value decreases with increasing temperature, and temperature changes will cause large resistance changes [13].

For the smoke sensor, there is a resistance wire made of a special material inside the smoke sensor. The resistance wire is usually heated by current. When encountering certain gases, the resistance wire will be processed because of the temperature decrease or increase of these gases.

2.2. Fire alarm principle

The traditional fire detection algorithm is used for a single temperature and smoke sensor. By setting a threshold, and then comparing the detected fire signal with this threshold, when the fire signal value exceeds the threshold, an alarm signal is generated. Assuming that the input signal of the algorithm is \( x(t) \), the commonly used threshold method is expressed by formula (1) and formula (2):

\[
y(t) = T[x(t)]
\]

\[
y(t) = \frac{dx(t)}{dt}
\]

In equation (1), \( T[x(t)] \) is the signal conversion function, and equation (2) compares the change rate with the set threshold. \( s \) is the set threshold, when \( y(t) \geq s \) is judged as fire, otherwise there is no fire.

When a fire occurs, observe the analog output of the smoke and temperature sensors, and you can see that there is a clear trend. A trend algorithm is proposed to transform the fire trend into a value of 0 or 1 through a step function [14-15]. The formula is shown in equations (3) and (4), \( n \) represents a certain moment, \( N \) is the length of the data window to be observed, \( u(n) \) is the unit step function, \( x(n) \) is the analog voltage output of the sensor.

\[
y(n) = \sum_{i=0}^{N-1} \sum_{j=i}^{N-1} u(x(n-i) - x(n-j))
\]

\[
\tau(n) = \frac{y(n)}{\max[y(n)]} = \frac{y(n)}{N(N+1)/2}
\]

In the above formula, \( \tau \) is the corresponding trend value threshold. The key point of this algorithm lies in the selection of parameter \( N \) and threshold \( s \). If the setting of window length \( N \) is small, it will
easily cause false alarms. If the setting is large, it will increase the detection time and reduce the sensitivity. The improper choice of $s$ will directly affect the reliability of the algorithm.

Various principles can detect fires, but they are susceptible to environmental factors and often produce false alarms. Therefore, it is a trend to use multi-sensor fusion and intelligent algorithms for fire detection.

3. System hardware design

This paper uses multi-sensor fusion to enhance the reliability of the detection system. The design of the fire alarm hardware system is mainly divided into a data acquisition module and a data processing module. The signal block diagram is shown in Figure 1. Among them, the smoke, CO, temperature and other conditions are converted into electrical signals through the signal acquisition circuit, and then sent to the processor through AD sampling for neural network fusion judgment. The calculated fire probability is output to the TFT screen, through the final threshold judgment will output the judgment value to the sound and light warning equipment at TTL level for fire alarm. Among them, use DS18B20 as the temperature sensor, the temperature range is $-55^\circ\text{C} - 125^\circ\text{C}$; use MQ-2 smoke gas sensor and MQ-7 carbon monoxide sensor, the detection concentration is 300–10000ppm; the above three sensors are used as signal input. Environmental conditions such as smoke, CO, and temperature pass through sensors and are converted into voltage signals which are easy to detect.

The processor selects ST's STM32F407 series chip, which has a 12-bit ADC inside. It can quantize the analog voltage output by the sensor to obtain a voltage value with an accuracy of 1mv. The chip also has a FPU (Float Point Unit, floating point arithmetic unit), which can accelerate the calculation of floating-point numbers. The display interface uses a 3.2-inch TFT LCD screen to display the measured data of the sensor and the probability of fire in real time.

![Figure 1. Signal flow diagram.](image)

Like most animals, humans have five senses, each based on complex and complex bioelectrical/optical and mechanical systems. The development of sensors and sensor technology in practical applications is based on the general principle of sensing and observing output in some easy-to-understand form. The development of sensors and sensor technology in practical applications is based on the general principle of sensing and observing output in some easy-to-understand forms [16].

The sensor converts the information of the object to be detected from non-electricity to electrical output, which is generally composed of sensitive elements, conversion elements, conversion circuits, and signal conditioning circuits. It can convert specific information of the environment where the sensor is located into electrical signals. MQ type sensor belongs to tin dioxide semiconductor gas sensitive material and belongs to surface ion type N type semiconductor. Tin dioxide absorbs oxygen in the air, forming negative ion adsorption of oxygen, which reduces the electron density in the semiconductor, thereby increasing its resistance value. When in contact with smoke or CO, if the
barrier at the grain boundary is adjusted by the smoke, it will cause a change in the surface conductivity. Using this point, you can obtain information about the presence of these smoke. The greater the concentration of smoke, the greater the conductivity, and the lower the output resistance, the greater the output analog signal.

4. GA-BP neural network

4.1. BP neural network

BP (Back Propagation, BP) neural network is a feedforward network trained according to error back propagation. It is mainly used in data fitting and function approximation. It is one of the most widely used neural network models. The network usually contains an input layer and an output layer, as well as more than one hidden layer. Its main feature is the forward transmission of the signal and the backward transmission of the error. In the forward transfer process, the input signal is processed layer by layer from the input layer through the hidden layer to the output layer. The neuron state of the current layer only affects the state of the next layer of neurons. If the output does not match the expectation, it will be backpropagation, and the network weights and thresholds will be adjusted according to the prediction error, so that the predicted output of the network will gradually approach the expected output [17].

Firstly, in this paper, a standard three-layer neural network is selected, which has an input layer, a hidden layer, and an output layer. However, the choice of activation function is currently based on experience and experiment. Secondly, in the initial stage of modeling, we tried different types of activation functions by substitution, such as Sigmoid, Tanh, Purelin, and Relu. Finally, the activation function combination with the highest classification accuracy is selected, that is, the hidden layer activation function is "tansig", and the output layer activation function is "tansig".

Existing research on the number of BP neural network layers shows that a three-layer neural network with an input layer, a hidden layer, and an output layer can approximate any function when there are enough hidden layer nodes. The common practice is to train the same sample set with different number of hidden layer nodes, and select the number of hidden layer nodes that minimize the network error. Generally based on formula (5):

$$L = \sqrt{M + O + \alpha}$$

(5)

Where \(M\) is the number of neurons in the input layer, \(O\) is the number of neurons in the output layer, \(\alpha\) is a number from 1 to 10, and \(L\) is the number of neurons in the hidden layer.

Let the output of the input layer neuron be \((x_1, x_2, ..., x_M)\), the input of the hidden layer neuron is \((z_1, z_2, ..., z_l)\), and the output of the hidden layer neuron is \((y_1, y_2, ..., y_L)\), the input of the neurons in the output layer is \((s_1, s_2, ..., s_O)\), and the output of the neurons in the output layer is \((out_1, out_2, ..., out_O)\). Therefore, the relational expression of the neural network is shown in (6)-(9):

$$z_j = \sum_{i=1}^{M} w_{j,i} * x_i + a_j; \quad 1 \leq j \leq L$$

(6)

$$y_j = \Phi(z_j)$$

(7)

$$s_k = \sum_{j=1}^{L} w_{k,j} * y_j + b_k; \quad 1 \leq k \leq O$$

(8)

$$out_k = \Psi(s_k)$$

(9)

Where \(w_{j,i}\) is the weight of the input layer to the hidden layer, \(w_{k,j}\) is the weight of the hidden layer to the output layer, \(a_j\) is the threshold of the input layer to the hidden layer, and \(b_k\) is the
hidden threshold value from layer to output layer, $\phi(x)$ is the activation function of the hidden layer, and $\Psi(x)$ is the output layer to the activation function.

The training samples are $A = \{(input^i, output^i)|i = 1, 2, \ldots, n\}$, $n$ is the number of samples, and $input^i$ represents the input of training data of group $i$, $output^i$ represents the expected output of the $i$-th training data, $output_k^i$ represents the expected output of the $k$-th neuron, $q^i$ represents the actual output of the $i$-th training data, and $q_k^i$ represents the actual output of the $k$-th neuron. Therefore, the error function is expressed as (10):

$$E = \frac{1}{2} \sum_{i=1}^{n} \sum_{k}^{o} (q_k^i - output_i)^2$$

(10)

The neural network structure used in this paper is shown in Figure 2. The three data (smoke, CO, temperature) obtained by the sensor are used as the input layer. Since smoldering fire and open flame belong to the category of fire, there is only one output (the output layer has only one nerve Yuan, output fire probability).

Before BP neural network simulation, it usually needs to first select the training set and test set. The role of the training set is to understand the characteristics and distribution of the data through system learning, so the training sample data should select the most general and representative data.

4.2. Genetic algorithm

Neural networks are often based on the principle of gradient descent, so there is a possibility of falling into a local optimal solution. As we all known, the natural heuristic algorithm has proved its effectiveness and ability to generate the best artificial neural networks parameters, rules and topologies over traditional algorithms. These traditional artificial neural networks parameters, rules and topologies are in solution quality, computational cost and avoidance the local minimum provides the best classification performance [18].

Genetic algorithm is a search heuristic that mimics the natural evolution process and is usually used to generate useful solutions for optimization and search problems. The basic genetic operators are selection, hybridization and mutation in genetic inheritance. Research on neural networks modeling found that, as a type of optimization program, genetic algorithms are good at finding the values close to the global optimal in large complex spaces in an intelligent manner [12,19-20].

Genetic algorithm (GA) is a commonly used global optimization algorithm with strong global search capabilities. Therefore, we use genetic algorithms to optimize the BP neural network and obtain the GA-BP neural network model. Each individual in the genetic algorithm population contains all the
weights and thresholds of a network, and the fitness value of each individual is calculated by the fitness function. In each iteration, the individual is adjusted through selection, crossover and mutation operations, and finally the individual corresponding to the optimal fitness value is found to realize the optimization of the neural network. However, the solution obtained by GA algorithm iteration will oscillate near the optimal solution. This is caused by the cross mutation of GA, and it is difficult to obtain an accurate optimal solution. Therefore, neural network training is required to make the solution accurate.

The fitness value used for genetic algorithm training is as follows. The output value $q_k^l$ of the neural network is compared with the actual output value $output_k^l$, and the second norm is taken as the fitness value $F$, as shown in equation (11) Show:

$$F = ||q_k^l - output_k^l||^2$$  (11)

The GA-BP algorithm used in this paper is to use the BP neural network as a classifier and the GA algorithm to optimize the BP neural network. From experimental simulations, it can be seen that the algorithm is more robust and improves its generalization ability.

The flow chart of the algorithm is shown in Figure 3. The implementation steps are as follows: ① input the pre-marked data and perform preprocessing; ② generate 50 populations, each individual encodes the chromosome, and the first 1-15 of chromosomes are written as the weights from input layer to hidden layer, and 16-20 are written as the weights from hidden layer to output layer, 21-25 are written as the thresholds from the input layer to the hidden layer, and the 26th is written as the threshold from the hidden layer to the output layer. ③ Selection and crossover: Calculate the fitness of 50 samples, and get the probability that 50 samples can reproduce. According to the probability that each sample can reproduce, two are selected as parents, and the chromosomes of the two parents are randomly exchanged to obtain new offspring. Repeat 50 times to get new children. ④ Mutation: mutate the chromosome of the offspring, that is, randomly add a random number between (-0.09, 0.09). ⑤ Repeat steps 3 and 4 until the end condition is reached (iteration to a certain number of times), the optimal individual is decoded, and the approximate global optimal solution is obtained by the GA algorithm. ⑥ Construct a 3-5-1 neural network model, assign the solution obtained by the GA algorithm to the weights and thresholds of the neural network, and select the tansig function for the activation functions of the hidden layer and the output layer. ⑦ Select the learning rate lr, target accuracy e, and start training. ⑧ When the end condition is reached, the BP neural network obtains the optimal weight and threshold.
5. Simulation experiment and analysis

The experiment of the detector is mainly composed of fire data simulation, GA-BP neural network processing data, and transplantation terminal.

5.1. Fire data simulation

FDS is a version of the field model software developed by the Building and Fire Research Laboratory (BFRL) based on the CFD analysis program for fire smoke diffusion simulation. It can simulate the relevant smoke velocity, smoke temperature and smoke flow conditions. FDS is affiliated with the National Institute of Standards and Technology (NIST). The software uses the grid as the minimum calculation unit and uses a numerical method to solve the N-S equation related to the lower Mach number flow driven by fire buoyancy, especially when calculating the mass and heat transfer of flue gas [21-22].

The fire simulation software FDS is composed of FDS and Smokeview. Among them, FDS is the main body of the software, which is mainly used for modeling and calculation of fire scenes. Smokeview acts as a visualization program for FDS calculations, and can perform dynamic data processing and static data display, and these data can be displayed in 2 or 3 dimensions [23].

Carry out simulation experiments on the sensing information (smoke, temperature, CO concentration in the air, etc.). Collect smoke, CO and temperature data, and process it to get training and test data of BP neural network. The modeling is shown in Fig. 4, setting a small room of 4*4*3, the grid is divided into 40*40*30, and the total number of grids is 48000. The smoke, CO and
temperature detection points are placed in the same grid at the corner of the house, the burner is placed in the middle of the house, and a window is set on the side.

![Fire scene modelling](image)

Figure 4. Fire scene modelling.

After the simulation, the combustion reaction test of propane, wood, polyurethane, ethanol and methane was carried out. Test results:

1. Propane burning produces smoke, CO gas and the temperature rises, and the CO spreads quickly. When the heat and smoke do not reach the detector, they have already reached the detector.
2. Wood and ethanol produce CO and the temperature rises. CO first reaches the detector, and the temperature transfer lags behind CO.
3. The burning of polyurethane produces a lot of smoke, the flame is not obvious, and the temperature and smoke rise almost simultaneously.
4. Methane combustion does not produce smoke and CO, only the temperature rises.

After obtaining the smoke and CO concentration data, it is converted into a voltage value that is easy to measure according to the characteristic curve of the sensor, and the temperature value is measured. Therefore, the obtained CO voltage, smoke voltage and temperature value are used as the input of the sensor's neural network.

5.2. GA-BP neural network processing data

When using BP neural network experiments, it often happens that the error is difficult to decrease, the accuracy rate fluctuates and the iteration time is too long, so the GA algorithm is used for optimization first. The PC uses simulated data to train the GA-BP neural network, and the development environment is MATLAB2018. Initially select the number of iterations \( N = 100 \), select the number of population \( n = 50 \). It can be seen from Figure 5 that when the GA algorithm reaches about 65 iterations, the mean square error value stabilizes near 106.499, the fitness value stabilizes after the 65th iteration, and the maximum fitness value tends to \( 9.389 \times 10^{-3} \).
Figure 5. Mean square error and Fitness of each iteration of GA algorithm when n=50 and N=100.

Assign the approximate global optimal weights and thresholds calculated by the GA algorithm to the neural network, set the learning rate \( lr = 0.03 \), target accuracy \( \epsilon = 10^{-7} \), select 636 representative samples for training, and obtain the training results. As shown in Figure 6, the abscissa is the number of iterations, and the ordinate is the mean square error. The mean square error has been on a good trend. It can be seen from the results that after 35 iterations, the performance of the entire network reaches 7.9*10^{-8} about. The correlation coefficient \( R=1 \) of the network training, as can be seen from the fitting effect shown in Figure 7, the training data classification effect is good.

Figure 6. Iterative mean square error decline curve of bp neural network.
Using 8654 test data GA-BP algorithm for testing, as shown in Figure 8, for the test set prediction results, the algorithm classification results and the correct results completely overlap, the test set accuracy rate reached 100%, and the effect is good.

Then compare the difference between the GA-BP algorithm prediction probability and the true value, but in actual application, there will be various external environments that interfere with the sensor or line, resulting in input fluctuations. The gap between the true values is as small as possible. As shown in Figure 9, the error of GA-BP network prediction is very small, and the absolute error is only 0.006. It can be seen that the system constructed by GA-BP neural network has better effect and higher reliability.

**Figure 7.** Network performance results.

**Figure 8.** Test set prediction results.
Figure 9. Sample prediction error.

\( w_{j,i} \) is the weight of the input layer to the hidden layer, \( w_{k,j} \) is the weight of the hidden layer to the output layer, \( a_j \) is the threshold of the input layer to the hidden layer, \( b_k \) is the hidden layer. To the threshold of the output layer, the neural network in this paper operates in a 3-5-1 structure, so \( i=1, 2, 3, j=1, 2, 3, 4, 5, k=1 \). The final weight and threshold data are:

\[
\begin{bmatrix}
-49.2286 & 0.4466 & -47.9673 \\
0.7887 & 0.5882 & 0.1029 \\
89.9686 & 28.6245 & -0.4684 \\
0.9033 & 0.1913 & -4.8108 \\
-0.5698 & 0.6820 & 0.2449
\end{bmatrix}
\]

\[
w_{k,j} = \begin{bmatrix}
-14.5634 & 30.2342 & 90.3726 & 11.6994 & 31.5679 \\
112.3391 & 0.0289 & -1577.1454 & 12.8504 & -0.2118
\end{bmatrix}
\]

\[
a_j = \begin{bmatrix}
31.4344
\end{bmatrix}
\]

5.3. transplant terminal

After obtaining the network parameters on the PC, using the CO and smoke sensor to connect the internal ADC of the STM32. The sensor outputs the voltage according to the concentration. After the sensor converts the environmental conditions to the voltage, it enters the AD conversion circuit, reads the data, and stores it in the STM32 register. The temperature sensor directly reads the data and stores it in the register according to the communication protocol. The actual system is shown in Figure 10, and the neural network parameters are fixed on the STM32 through programming. Finally, the probability of fire discrimination is obtained. The real-time performance is good and the accuracy is high.
6. Conclusion
This paper proposes a high-precision fire alarm system, which uses FDS software to simulate fire data, uses genetic algorithms to optimize the parameters of the neural network, and then trains the neural network to use the network output as a fire discrimination result. Compared with the traditional linear fitting algorithm, the GA-BP algorithm can obtain more accurate fire detection results. The result shows that the fire alarm correct rate of GA-BP algorithm is 100%. At the same time, the system can also enhance the system's resistance to external uncertainties, and enhance the reliability of the fire alarm system. In addition, the algorithm can put the process of the neural network algorithm on the MCU to run, and obtain high-precision measurement results directly on the fire detection system, which can provide a certain reference for the related design of the simple neural network transplantation terminal.

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