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Research Article

Multisensor-Weighted Fusion Algorithm Based on Improved AHP for Aircraft Fire Detection

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Aiming at the high false alarm rate when using single sensor to detect fire in aircraft cabin, a multisensor data fusion method is proposed to detect fire. First, the weights of multiple factors, that is, temperature, smoke concentration, CO concentration, and infrared ray intensity in the event of fire, were calculated by using the improved analytic hierarchy process (AHP) method on each sensor node of wireless sensor network, and the probability of fire event in the cabin was evaluated by multivariable-weighted fusion method. Second, based on the mutual support among the evaluation data of fire probabilities of each node, the adaptive weight coefficient is assigned to each evaluation value, and the weighted fusion of all evaluation values of each node is conducted to obtain the fire probability. In the end, compared to the threshold of probability, the fire alarm is determined. Comparing the proposed algorithm to the grey fuzzy neural network fusion algorithm and fuzzy logic fusion algorithm in terms of the time consumption for fire detection and sending alarm and the accuracy of fire alarm perspectives, the experiments demonstrate that the proposed fire detection algorithm can detect the fire within 10*s* and reduce the false alarm rate to less than 0.5%, which verifies the superiority of the algorithm in promptness and accuracy. In the meanwhile, the fault tolerance of the algorithm is proved as well.

1. Introduction

It is well known that safety is always the priority for aircrafts flights; furthermore, fire is a big threat for flight safety. Therefore, fire detection issues for aircrafts have become the focus for aircraft environmental monitoring. It is necessary to develop an effective method to realize the real-time and effective monitoring of cabin environments and provide the timely and accurate alarm for emergencies. Tracking and estimating the target system can effectively monitor the system condition [1–3]. At present, fire alarm method can only make alarm decision based on specific parameters (such as temperature, smoke, fire, and gas), which is vulnerable to external interferences and often gives false alarm [4]. For example, when the dust particles in the cabin reach a certain concentration, the sensor will mistakenly consider them as flame smokes and then send an alarm signal. There are multiple false fire alarms for the aircraft industrial applications. For example, on March 4, 2019, a Boeing 777 flying from Beijing to Los Angeles made an emergency landing at Russia's Anadyr Airport because a fire alarm broke out in the rear cargo compartment during flight. Unfortunately, after inspections, the cargo hold was normal and there was no sign of fire. At the end, it was concluded that the aircraft fire information was out of order. Once the fire alarm signal is sent, an emergency landing is required. Therefore, false fire alarms definitely affect the safety, increase the burden of crew works, and bring about more economy loss for civil aviation industry. In the future, aircraft manufacturing will develop towards flying wirelessly instead of flying by wire; therefore, it will become a trend to use WSN technology for aircraft cabin or cargo environment monitoring. For example, Wang et al. utilized the distributed wireless sensor monitoring network to monitor and estimate multiple contaminants and overcome the hypersensitivity of the single sensor in aircraft cabins [5, 6]. Currently, WSN-based multisensor indoor fire detection technology usually uses the data detected by multiple sensors to fuse and obtain the probability of fire event, which greatly improves the accuracy of fire alarms. General methods of multisensor data fusion include fuzzy logic fusion based on neural network [7], fuzzy logic fusion [8], and D-S evidence inference [9]. The above method fuses the environmental information collected by temperature sensor, smoke sensor, CO gas sensor, and flame infrared ray sensor, effectively improving the accuracy of fire detection.

The above commonly used fusion algorithms mainly rely on the establishment of fuzzy reasoning rules and the construction of neural networks. Although the detection accuracy is greatly improved to some extent when the input variables are increased, the detection and decision time becomes longer. However, China civil aviation regulations article 25.858 states that the fire alarm should be notified to the flight crew by visual indication in less than one minute. Therefore, it is necessary to design a method to more accurately and timely determine the fire alarm when fusing multiple variables. Some existing literatures demonstrate that the fuzzy logic fusion algorithm based on neural network can make the fusion result close to the real result by means of connecting weights between training networks [10, 11]. However, when the input variable increases, the number of network layers increases, the data set to be trained increases, and the detection time increases. In order to shorten the fusion time to some extent, the weight of each fusion variable in the probability assessment of fire event can be considered; then, the sensor data can be estimated. Among them, analytic hierarchy process (AHP) is widely used in multivariable weight calculation and system state evaluation [12–15]. For example, Yang et al. used fuzzy AHP and deviation maximization method to determine the subjective and objective weight of each index and evaluated the risk degree of voltage sag of each observation point by weighting the comprehensive weight and its pressure drop, so as to take corresponding measures timely [12].

Various fusion methods introduced above are all under the assumption that the sensors work normally under the ideal conditions for fire alarm system; however, environmental complexity and uncertainty often cause sensor malfunctions, further cause the large deviation, and seriously affect the fusion result. In order to avoid the above problem, relevant works have been conducted partly in the following researches. Yu et al. defined the relationship between data as conditional function dependence and microfunction dependence, so as to avoid inaccuracy caused by inconsistency of data to a certain extent [16]. Yang et al. proposed a multisensor weighted fusion method based on augmented support matrix to avoid the low fusion accuracy [17].

The main contributions of this paper are conducted from the promptness and accuracy requirement for the aircraft environment, respectively. First, this paper designs a new "multivariable-weighted fusion" fire assessment algorithm based on the improved AHP. Therefore, the algorithm can quickly detect the fire situation when fusing variables simultaneously and greatly reduce the false alarm rate. Second, this paper develops an adaptive-weighted fusion method to fuse the multiple variables for each sensor node when some sensors malfunction. By constructing the support degree matrix as the adaptive distribution weight coefficient of each node, to a certain extent, the proposed method avoids the low fusion accuracy due to the measurement deviation coming from the faulty sensors.

The structure of this paper is arranged as follows. The first section is the introduction. In Section 2, an improved AHP and multivariable-weighted fusion algorithm are introduced to evaluate the probability of fire event for each sensor node. Section 3 proposes an adaptive-weighted fusion method to evaluate the probability of fire event of all nodes when some sensors malfunction. Section 4 presents the simulation experiments verifying the accuracy, fast response, and fault tolerance of the proposed algorithm. The conclusion of this paper is drawn in Section 5.

2. A Fire Assessment Algorithm Based on a Multivariable-Weighted Fusion

In this section, an improved AHP method is studied and a multivariable weight calculation method is proposed to determine the weight of temperature, smoke concentration, CO concentration, and infrared ray intensity for fire event. A new "multivariable-weighted fusion" algorithm is proposed at each sensor node of WSN to obtain the evaluation value of each node on the probability of fire event in the cabin.

2.1. Multivariable Weight Calculation Based on Improved AHP Method. To evaluate and judge the fire events in aircrafts, it is necessary to determine weight of the relevant variables scientifically and reasonably for the fire evaluation process. This paper mainly adopts the improved AHP method to determine the weight of variables [18]. In traditional AHP, the weight of influencing factors in event decision-making is obtained by selecting a reasonable judgment matrix. However, due to the randomness of judgment matrix selection, the calculated weight may be deviated from the actual weight. In order to ensure that the obtained weights can reflect the influence degree of variables more accurately, the improved AHP calculates the optimal weight of variables in the weight interval by selecting several reasonable judgment matrices. The optimal weight is closer to the actual influence degree of variables.

The basic process of the improved AHP method for evaluating fire events is introduced as follows:

Step 1: suppose that the variables determining the fire event probability are temperature, smoke concentration, CO concentration, and infrared ray intensity. The variables are expressed as $x_i\,(i = 1, 2, 3, 4)$ and i is the subscript of the variable. denote x_1 as the temperature, x_2 as the smoke concentration, x_3 as the CO concentration, and x_4 as the infrared light intensity.

Step 2: establish the judgment matrix.

The influence degree relation between variables is expressed quantitatively by the judgment matrix. Let the judgment matrix be $C\varepsilon R^{n\times n}$, where n represents the number of variables [19].

The form of the judgment matrix C is

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix}. \tag{1}$$

The matrix element, $c_{ij} = x_i/x_j$ (i and j are the variable indexes), represents the importance degree for variables determining the probability of fire event.

The rule for determining element c_{ij} is shown below:

If x_i and x_j are equally important, then $c_{ij} = 1$ and $c_{ji} = 1$
If x_i is slightly more important than x_j, then $c_{ij} = 3$ and $c_{ji} = 1/3$
If x_i is obviously more important than x_j, then $c_{ij} = 5$ and $c_{ji} = 1/5$
If x_i is much more important than x_j, then $c_{ij} = 7$ and $c_{ji} = 1/7$
If x_i is absolutely more important than x_j, then $c_{ij} = 9$ and $c_{ji} = 1/9$

If the importance relationship for x_i and x_j is located between the relationships illustrated above, c_{ij} can also select 2, 4, 6, and 8. In fact, the element c_{ij} can be any integer between 1 and 9 [20].

Step 3: check the consistency of the judgment matrix.

In this paper, the improved AHP can calculate the optimal weight of each variable by selecting multiple judgment matrices. In order to avoid a large error between the weights obtained, the consistency of C should be tested. When the judgment matrix C is completely consistent, $c_{ij} = 1$, $\sum_{i=1}^{n} \lambda_i = \sum_{i=1}^{n} c_{ij} = n$ (λ is the eigenvalue of matrix C), a unique nonzero $\lambda = \lambda_{\max} = n$ exists. When the judgment matrix is inconsistent, $\lambda_{\max} \geq n$.

At this moment,

$$\lambda_{\max} + \sum_{i\neq \max}^{n} \lambda_i = \sum_{i=1}^{n} n. \tag{2}$$

Then,

$$\lambda_{\max} - n = -\sum_{i\neq \max}^{n} \lambda_i. \tag{3}$$

The average value is used as the index to test the consistency of judgment matrix:

$$\text{C.I.} = \frac{\lambda_{\max} - n}{n-1} = \frac{-\sum_{i=\max}\lambda_{\max}}{n-1}. \tag{4}$$

When $\lambda_{\max} = n$ and $C.I. = 0$, C can be judged to be exactly consensus. The larger the $C.I.$ is, the worse the consistency of the judgment matrix will be. Generally, it is only required that the consistency of the matrix be reasonable if $\text{C.I.} \leq 0.1$.

The consistency of the judgment matrix is related to its dimension. The greater the dimension n of the judgment matrix is, the worse the consistency of the judgment matrix is. Therefore, the consistency requirement of high-dimensional judgment matrix should be relaxed. In this case, the modified RI (RI values are listed in Table 1 [21]) can be introduced and the more reasonable value, $C.R.$, can be taken as the index to measure the consistency of the judgment matrix. When $C.R. < 0.1$, it is generally considered that the consistency of the judgment matrix is acceptable.

Step 4: calculate the weight intervals of variables by using the eigenvector method.

Based on the judgment matrix constructed above, the weight of each variable was calculated by the eigenvector method, and the calculated weight was written into the form of interval, denoted as the weight interval of the variable (the interval is composed of independent weight points).

After arbitrarily selecting a reasonable judgment matrix, a weight of variable can be calculated according to the eigenvector method. The calculation formulas are listed as follows [22]:

$$M_{i,k} = \prod_{j=1}^{n} c_{ij,k}, \tag{5}$$

$$W_{i,k} = \sqrt[n]{M_{i,k}}, \tag{6}$$

$$\overrightarrow{W}_{i,k} = \frac{W_{i,k}}{\sum_{i=1}^{n} W_{i,k}}, \tag{7}$$

where i is the variable index ($i = 1, 2, 3, 4$) and k is the number of reasonably selected judgment matrices ($k \in N^{+}$). $\overrightarrow{W}_{i,k}$ is a weight value for the i^{th} variable under the k^{th} judgment matrix. So, there are k weights for each variable i.

The k weights of each variable obtained above are written in the form of interval, which is the weight interval of the variable. For any variable i, selecting k judgment matrices, a weight interval of variable i can be obtained by using formulas (5)–(7), and the interval contains k weights.

Step 5: obtain the optimal weight.

The optimal weight fully considers all weights during the weight interval so as to ensure that the final evaluation result can better reflect the actual situations. At the same time, the optimal weight fusion can effectively avoid the tedious calculation process in fusion and improve the response speed of fire event evaluation. Suppose that W_i represents a

Table 1: *RI* values under different orders of judgment matrices.

The order of the matrix	RI
1	0
2	0
3	0.52
4	0.89
5	1.12
6	1.26
7	1.36
8	1.41

weight of the variable i, and the reasonable judgment matrix is $m (m \in N^{+})$; the objective function is constructed as

$$\min \sum_{i=1}^{4} \sum_{k=1}^{m} \left(\overrightarrow{W}_{i,k} - w_i \right)^2. \tag{8}$$

The constraint condition of the objective function is

$$\sum_{i=1}^{4} w_i = 1. \tag{9}$$

Based on formulas (8) and (9), the optimal weight of the i^{th} variable is denoted as w_i^*.

2.2. Fire Probability Assessment Algorithm Based on Variable-Weighted Fusion. According to the actual value of each variable in different environments, the interval of temperature (°C) is set in the range of [0, 100], smoke concentration (ppm) is located in the range of [100, 1000], CO concentration (ppm) lies in the range of [10, 100], and infrared ray intensity (lux) is placed in the range of [100, 1000]. Each variable range is normalized in the range of [0-] by using the following formula [23]:

$$x_i^* = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \tag{10}$$

where $\max(x_i)$ is the maximum value for variable i and $\min(x_i)$ is the minimum value for variable i.

Suppose N sensor nodes are deployed in the aircraft, the normalized variable value is denoted as $x_i^* \, (i = 1, 2, 3, 4)$, the optimal weight of the variable is $w_i^* \, (i = 1, 2, 3, 4)$, the weighted result of variables is the fire probability, and the calculation formula is

$$p_{i^*} = \sum_{i=1}^{4} x_i^* w_i^*, \quad i^* \varepsilon 1, 2, \ldots, N, \tag{11}$$

where p_{i*} is the assessment result of the probability of fire for node i^*.

3. An Adaptive-Weighted Fusion Algorithm Based on Support Degree Matrix

In order to ensure the accuracy of fire alarm, it is necessary to adaptively fuse the fire probability values coming from each node. At the same time, in order to avoid the impact resulting from sensor failures on the accuracy of fusion results, this section proposes an adaptive-weighted fusion algorithm based on support degree matrix. This algorithm can objectively demonstrate the support degree among each node data and even the unknown assessment ability of the fire event probability for each node. By constructing the augmented matrix, the weight coefficients of fire probability assessment for each node are adaptively adjusted in order to achieve the best fusion. The characteristics of this algorithm include online data fusion for a large amount of data as well as better fault tolerant capability by adaptively allocating the weight coefficients according to the reliability.

3.1. Support Degree Matrix Construction. Assume that there are N sensor nodes (each node is composed of temperature, smoke concentration, CO concentration, and intensity of the infrared light sensors) to measure the environment variables and calculate the fire event probability. Let $p_i * (k)$ and $p_j * (k)$ represent the fire event probability evaluation values of sensor nodes i^* and j^* $(i^*, j^* \epsilon (1, 2, \ldots, N))$ at the moment k, respectively. When the difference between $p_i * (k)$ and $p_j * (k)$ is too large, these two sensor nodes do not support each other at time k. If the difference is small, it means that these two nodes support each other. If a node is supported by many nodes at the same time, it can be considered as a valid fire probability assessment value. Otherwise, the node will be assigned a lower weight during the fusion process.

Define a support degree function, $r_{i^* j^*}(k)$, which employs the exponential function in the fuzzy set to express the mutual support degree between $p_i * (k)$ and $p_j * (k)$:

$$r_{i^* j^*}(k) = \exp\left(-\alpha \cdot \left(p_{i^*}(k) - p_{j^*}(k) \right)^2 \right). \tag{12}$$

The parameter α can be adjusted in order to alter the fusion accuracy conveniently, generally set to 0.8 [17].

At the moment k, the mutual support degree of sensors i^* and j^* can be described in a matrix according to the support degree function $r_i * {}_j * (k)$:

$$R_N^{(k)} = \begin{bmatrix} 1 & r_{12}(k) & \cdots & r_{1N}(k) \\ r_{21}(k) & 1 & \cdots & r_{2N}(k) \\ \cdots & \cdots & \cdots & \cdots \\ r_{N1}(k) & r_{N2}(k) & \cdots & 1 \end{bmatrix}. \tag{13}$$

As for the elements in the $i^{*\,\text{th}}$ column of $R_N^{(k)}$, the bigger $\sum_{j^*=1}^{N} r_{i^* j^*}(k)$ is, the more reliable node i^* is, and vice versa.

3.2. Augmented Support Degree Matrix Construction. At each sampling time, the proposed method adds a new row and a new column in the original support degree matrix to integrate all the assessments and forms a new augmented support degree matrix. The newly inserted dimension aims at measuring the mutual support degree between all current assessments and previous assessments.

Augmented dimension can be obtained by the following steps:

(1) When $k = 1$, define the average of the first N assessment values $\overline{p}\,(1)$ as the initial estimate $\widehat{p}_0$.

(2) The augmented row and column at time k are

$$\begin{cases} r_{i^*(N+1)}(k) = \exp\left(-\alpha \cdot \left(p_{i^*} - \widehat{p}_{k-1}\right)^2\right), \\ r_{(N+1)j^*}(k) = \exp\left(-\alpha \cdot \left(\widehat{p}_{k-1} - p_{j^*}\right)^2\right), \\ r_{(N+1)(N+1)}(k) = 1, \end{cases} \tag{14}$$

where $\widehat{p}_{k-1}$ represents the fused result at time $(k-1)$.

(3) The following formula can be used to obtain the augmented support degree matrix at time k:

$$R_{N+1}^{(k)} = \begin{bmatrix} 1 & \cdots & r_{1N}(k) & r_{1(N+1)}(k) \\ \cdots & 1 & \cdots & \cdots \\ r_{N1}(k) & \cdots & 1 & r_{N(N+1)}(k) \\ r_{(N+1)1}(k) & \cdots & r_{(N+1)N}(k) & 1 \end{bmatrix}, \tag{15}$$

where $R_{N+1}^{(k)}$ is the integrated support degree of all the nodes at each sampling time.

3.3. Adaptive-Weighted Fusion Based on the Assessment Values of Each Node. Let $w_i * (k)$ denote the fusion weight coefficient of $p_i * (k)$ ($w_{N+1}(k)$ is the weight coefficient of the fusion result $\widehat{p}_{k-1}$ at the time of $(k-1)$); $w_i * (k)$ satisfies

$$\sum_{i^*=1}^{N+1} w_{i^*}(k) = 1, \quad 0 \le w_{i^*}(k) \le 1. \tag{16}$$

In the augmented support degree matrix, $R_{N+1}^{(k)}$, the weight coefficient of $p_i * (k)$ can be obtained by integrating the $i^{*\text{th}}$ column of $R_{N+1}^{(k)}$. Assume that there is a set of vectors, $b_{j^*}(k)$ ($j^* = 1, \ldots, N+1$), and each element is the result of integration with respect to $r_j *_i * (k)$ for i^*, and $w_i * (k)$ is

$$w_{i^*}(k) = b_1(k) r_{1i^*}(k) + \cdots + b_{N+1}(k) r_{(N+1)i^*}(k), \tag{17}$$

where $i^*, j^* = 1, 2, \ldots, N+1$.

According to (15), we rewrite (17) as

$$W = R_{N+1}^{(k)} B, \tag{18}$$

where $W = [w_1(k), w_2(k), \cdots, w_{N+1}(k)]^T$ and $B = [b_1(k), b_2(k), \cdots, b_{N+1}(k)]^T$.

Since $r_{i^*j^*}(k) \ge 0$, $R_{N+1}^{(k)}$ is a nonnegative symmetrical matrix and is based on Perron–Frobenius theorem, the maximum modulus eigenvalue λ^* can be calculated ($\lambda^* > 0$) [24].

Then,

$$\lambda^* B = R_{N+1}^{(k)} B. \tag{19}$$

Calculate the positive eigenvector B corresponding to λ^*:

$$W = \lambda^* B. \tag{20}$$

The weight coefficient is proportional to that of eigenvectors, and the relationship is shown in the following equation:

$$\frac{w_{i^*}(k)}{w_{j^*}(k)} = \frac{b_{i^*}(k)}{b_{j^*}(k)}. \tag{21}$$

According to (16), the weight coefficient of each node is

$$w_{i^*}(k) = \frac{b_{i^*}(k)}{b_1(k) + \cdots + b_{N+1}(k)} = \frac{b_{i^*}(k)}{\sum_{j^*=1}^{N+1} b_{j^*}(k)}, \tag{22}$$

where $i^*, j^* = 1, 2, \ldots N+1$.

Then, the final fusion expression is obtained by

$$\widehat{p}_k = \sum_{i^*=1}^{N+1} w_{i^*}(k) p_{i^*}(k) = \sum_{i^*=1}^{N+1} \frac{b_{i^*}(k)}{\sum_{j^*=1}^{N+1} b_{j^*}(k)} p_{i^*}(k), \tag{23}$$

where $\widehat{p}_k$ represents the fire event probability in the aircraft environment after data fusion. Comparing it to the fire threshold probability, if the probability is greater than the threshold, the system will send out a fire alarm signal.

According to [25, 26], the critical value of fire event is set as follows: temperature is 55°C, smoke concentration is 700 ppm, CO concentration is 20 ppm, and infrared light intensity is 760 lux. The above variables are normalized, and the result of the fire threshold probability is obtained by (11).

Two portions, online and offline fire event detection processes, are included in the proposed algorithm for aircraft cabins in the paper. The specific steps are listed in Figure 1. Steps 1 to 5 in the second section are used for the offline weight calculation, aiming at obtaining the weight of variable x_i ($i = 1, 2, 3, 4$). Furthermore, the online detection process includes three steps. First, the measured environmental variables are normalized by formula (10). Second, the fire probability is evaluated by formula (11) for each node. Third, use the adaptive-weighted fusion algorithm to calculate the actual fire probability $\widehat{p}_k$ in the aircraft and compare it with the threshold probability to determine whether a fire alarm is released or not (Figure 1).

4. Simulation Experiments Analysis

In this section, suppose that 50 sensor nodes are placed in aircraft cabin and cargo. Each node is composed of temperature, smoke concentration, CO concentration, and infrared ray intensity sensors. The deployment schematic diagram of nodes is shown in Figure 2. The environmental parameters collected at each node are $X^{i^*} = [x_1, x_2, x_3, x_4]$ ($i^* = 1, 2, \ldots, 50$), and the units for each variable are °C for temperature, ppm for smoke concentration and CO concentration, and lux for infrared ray intensity, respectively. Under the same experimental conditions, the proposed online fire detection algorithm is compared to the grey fuzzy neural network fusion algorithm in [7] and the fuzzy logic fusion algorithm in [8] to verify the superiority of online fire detection algorithm in terms of promptness, accuracy, and fault tolerance.

4.1. The Optimal Weight Calculation for Each Variable. As illustration about variable weights calculation in the second section, the assumptions about the influence degree ranking for each variable x_i ($i = 1, 2, 3, 4$) are placed as follows:

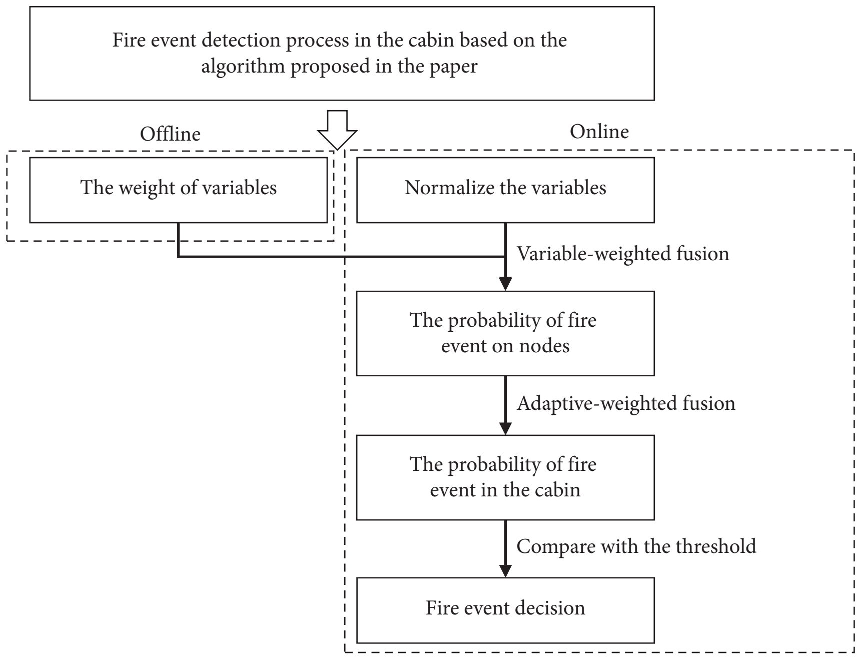

Figure 1: Fire detection flowchart.

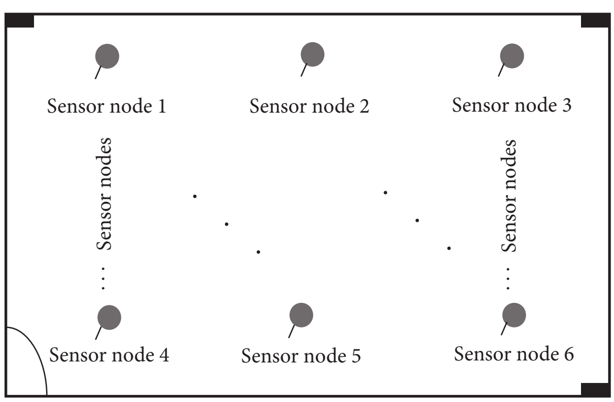

Figure 2: Schematic diagram of sensor node deployment for fire detection.

$$
\begin{aligned}
&\text{Assumption 1: } x_1 > x_2 > x_3 > x_4,\\
&\text{Assumption 2: } x_1 > x_2 > x_4 > x_3,\\
&\text{Assumption 3: } x_1 > x_3 > x_2 > x_4,\\
&\text{Assumption 4: } x_1 > x_3 > x_4 > x_2,\\
&\text{Assumption 5: } x_1 > x_4 > x_2 > x_3,\\
&\text{Assumption 6: } x_1 > x_4 > x_3 > x_2,\\
&\qquad\vdots\\
&\text{Assumtpion 24: } x_4 > x_3 > x_2 > x_1.
\end{aligned} \tag{24}
$$

There are 24 assumptions in total named as A1, A2, ... A24.

According to the assumptions given above, calculate the weight interval of each variable when k was 5 ($B_1 \sim B_5$ are judgment matrices) and the optimal weight of each variable within the weight interval based on formulas (8) and (9). Table 2 describes the process of weight interval calculation (take the weight interval obtained under assumption 13 as an example). Table 3 lists the optimal weight of each variable under all the assumptions.

Five groups of environmental parameters were selected in this experiment, that is, $X^1 = [38, 500, 18, 188]$, $X^2 = [89, 580, 30, 200]$, $X^3 = [39, 450, 70, 229]$, $X^4 = [51, 750, 38, 199]$, and $X^5 = [39, 480, 19, 705]$. Using the online detection algorithm under five groups of parameters, the fire event probabilities under A1, A2, ..., A24 are obtained, respectively. Under the same input condition, calculate the fire event probability under the assumptions of A1, A2, ..., A24 and compare it with the fire probability calculated by the fuzzy fusion algorithm based on the "IF THEN" rule shown in [8]. The curves shown in Figure 3 illustrate the error of the fire probabilities between the online algorithm under A1, A2, ..., A24 and the fuzzy fusion algorithm shown in [8], and Figure 3 demonstrates that the probability under A13 is close to that obtained by fuzzy fusion algorithm under the same condition.

4.2. Promptness and Accuracy Analysis of Online Detection Algorithm. From the perspective of the time requirement for fire detection and alarm signal issuance, this paper analyzes the promptness of the proposed online detection algorithm, the grey fuzzy neural network fusion algorithm in [7], and the fuzzy logic fusion algorithm in [8] about fire detection. The paper conducts 100 trials, and the parameters are randomly selected among the corresponding intervals, x_1 located in the interval (55, 100), x_2 placed in the interval (700, 1000), x_3 located in the interval (20, 100), and x_4 set in the interval (760, 1000). As can be seen in Figure 4, under the same input parameters, the proposed online detection algorithm can realize the fire alarm within 10s and 23s for the

Table 2: Calculation results of variable weight interval under A13.

Judgment matrices	$B_1 = \begin{bmatrix} 1 & 3 & 1/5 & 3 \\ 1/3 & 1 & 1/7 & 3 \\ 5 & 7 & 1 & 7 \\ 1/3 & 1/3 & 1/7 & 1 \end{bmatrix}$	$B_2 = \begin{bmatrix} 1 & 2 & 1/5 & 4 \\ 1/2 & 1 & 1/7 & 4 \\ 5 & 7 & 1 & 7 \\ 1/4 & 1/4 & 1/7 & 1 \end{bmatrix}$	$B_3 = \begin{bmatrix} 1 & 1 & 1/5 & 2 \\ 1 & 1 & 1/6 & 4 \\ 5 & 6 & 1 & 8 \\ 1/2 & 1/4 & 1/8 & 1 \end{bmatrix}$	$B_4 = \begin{bmatrix} 1 & 1 & 1/5 & 2 \\ 1 & 1 & 1/6 & 4 \\ 5 & 6 & 1 & 7 \\ 1/2 & 1/4 & 1/7 & 1 \end{bmatrix}$	$B_5 = \begin{bmatrix} 1 & 2 & 1/7 & 2 \\ 1/2 & 1 & 1/5 & 3 \\ 7 & 5 & 1 & 6 \\ 1/2 & 1/3 & 1/6 & 1 \end{bmatrix}$
The weight of x_1	0.1908	0.1587	0.1298	0.1314	0.1486
The weight of x_2	0.1032	0.1356	0.1533	0.1566	0.1301
The weight of x_3	0.6471	0.6493	0.6572	0.6490	0.6515
The weight of x_4	0.0589	0.0564	0.0597	0.0630	0.0698
Weight interval of x_1	[0.1298, 0.1314, 0.1486, 0.1587, 0.1908]				
Weight interval of x_2	[0.1032, 0.1301, 0.1356, 0.1533, 0.1566]				
Weight interval of x_3	[0.6471, 0.6490, 0.6493, 0.6515, 0.6572]				
Weight interval of x_4	[0.0564, 0.0589, 0.0597, 0.0630, 0.0698]				

Table 3: The output result of the optimal weight of each variable under all assumptions.

Variable weights (in x_1, x_2, x_3, x_4 order)			
A1	[0.6492, 0.1474, 0.1439, 0.0595]	A2	[0.6492, 0.1474, 0.0595, 0.1439]
A3	[0.6492, 0.1439, 0.1474, 0.0595]	A4	[0.6492, 0.0595, 0.1474, 0.1439]
A5	[0.6492, 0.1439, 0.0595, 0.1474]	A6	[0.1474, 0.6492, 0.1439, 0.0595]
A7	[0.1474, 0.6492, 0.1439, 0.0595]	A8	[0.1474, 0.6492, 0.0595, 0.1439]
A9	[0.1439, 0.6492, 0.1474, 0.0595]	A10	[0.0595, 0.6492, 0.1474, 0.1439]
A11	[0.1439, 0.6492, 0.0595, 0.1474]	A12	[0.0595, 0.6492, 0.1439, 0.1474]
A13	[0.1474, 0.1439, 0.6492, 0.0595]	A14	[0.1474, 0.0595, 0.6492, 0.1439]
A15	[0.1439, 0.1474, 0.6492, 0.0595]	A16	[0.0595, 0.1474, 0.6492, 0.1439]
A17	[0.1439, 0.0595, 0.6492, 0.1474]	A18	[0.0595, 0.1439, 0.6492, 0.1474]
A19	[0.1474, 0.1439, 0.0595, 0.6492]	A20	[0.1474, 0.0595, 0.1439, 0.6492]
A21	[0.1439, 0.1474, 0.0595, 0.6492]	A22	[0.0595, 0.1474, 0.1439, 0.6492]
A23	[0.1439, 0.0595, 0.1474, 0.6492]	A24	[0.0595, 0.1439, 0.1474, 0.6492]

grey fuzzy neural network fusion algorithm and within 20*s* for the fuzzy logic fusion algorithm. It is obvious that the online detection algorithm is superior to the other algorithms in the promptness of fire alarm under the same input parameters.

The core of the online detection algorithm is to calculate the weight of each variable. Take A13 as an example. A set of weights [0.6492, 0.1474, 0.1439, 0.0595] is selected when the number of judgment matrices, k, is 5. Figure 5 illustrates the relationship between the selected number of judgment matrices k and the false alarm rate of fire detection, where it is assumed that when k is 5, the false alarm rate of fire is 3% as the initial condition. It is easy to observe that the more reasonable number of judgment matrices is selected, the more accurate the fire event probability is. When k is greater than 20, the online detection algorithm reduces the false alarm rate to less than 0.5% and effectively improves the accuracy of fire alarm.

4.3. Fault Tolerance of Online Detection Algorithm Analysis. This subsection discusses the deviation of fire event probability when sensor faults occur by using the proposed method under the 50 sensor nodes' network. Assume that the parameters of the experimental conditions are as follows: ambient temperature is 38°C, the smoke concentration is 650 ppm, the CO concentration is 14 ppm, and the infrared ray intensity is 700 lux. When all nodes are working normally, the fire event probability is estimated by three methods as shown in Table 4. Correspondingly, these values are regarded as the reference true values for the fault tolerance analysis.

The error square (*SE*) is adopted as the standard to evaluate the detection accuracy of the above three algorithms defined as

$$\mathrm{SE}^j = \left(p^j - \widehat{p}^j\right)^2, \tag{25}$$

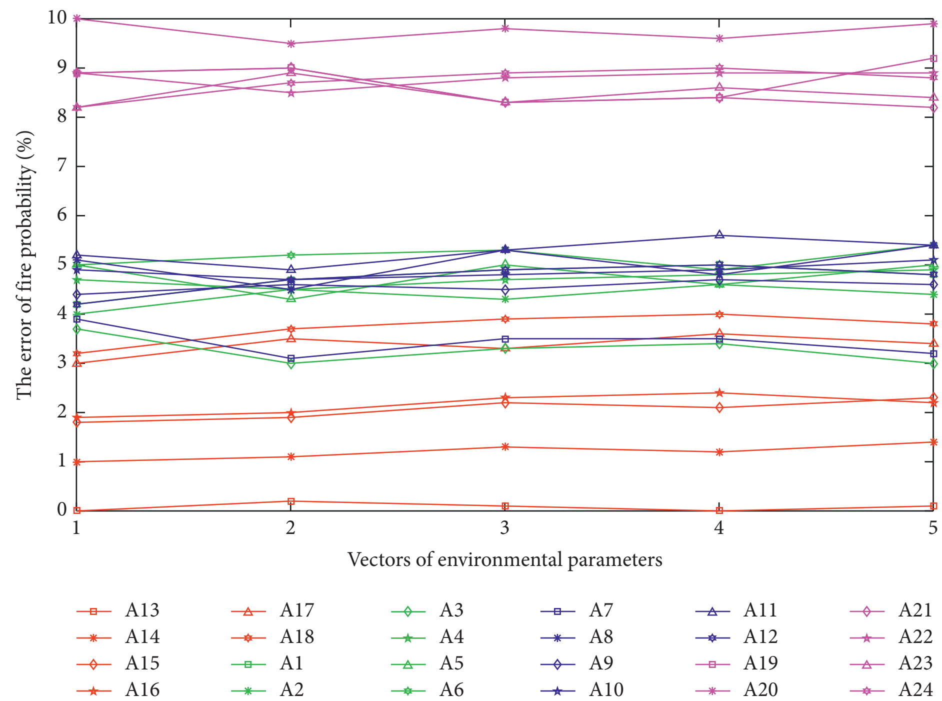

Figure 3: The error curve of fire probability.

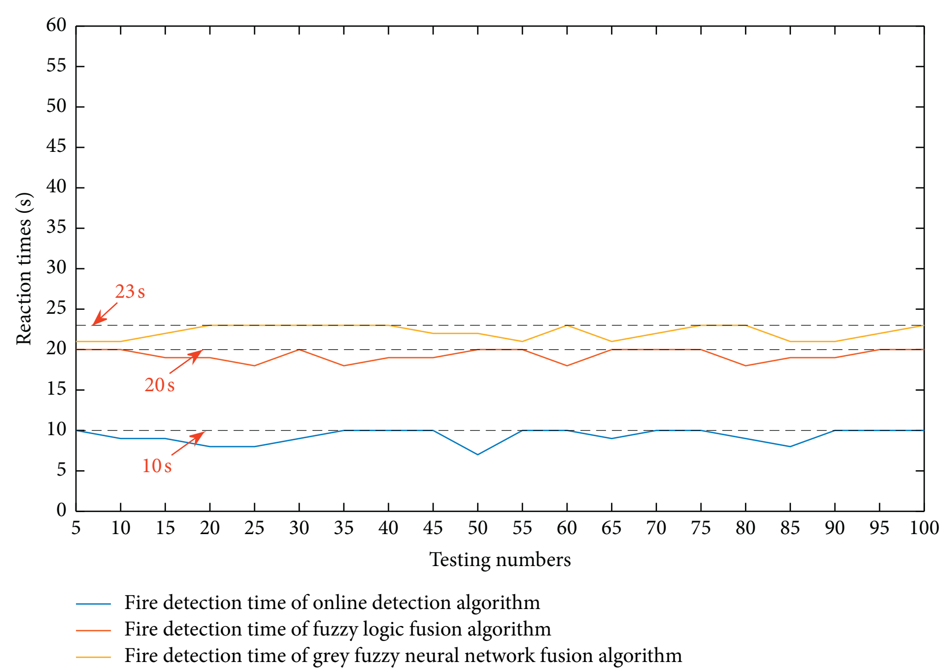

Figure 4: Comparison diagram of detection time of three fire detection algorithms.

where j is the subscript of detection algorithm ($j = 1, 2, 3$), p^j represents the reference value of fire probability under j algorithm, and $\widehat{p}^j$ represents the estimated fire event probability after fusion of 50 nodes under j^{th} algorithm.

Generally, when SE reaches 2, it is considered that a large deviation occurs, and the corresponding fire detection results become invalid. As seen from Figure 6, when the number of fault nodes reaches 10, the detection algorithms proposed by [7, 8] will become invalid and the detection accuracy of the algorithm will decrease sharply, which cannot meet the requirements of the practical application system. On the contrary, SE value calculated by the proposed method increases gently and a large deviation occurs only after the fault nodes reach 30 due to the adaptive-weighted fusion algorithm based on the mutual support degree matrix. Therefore, in the actual fire detection system, the fault

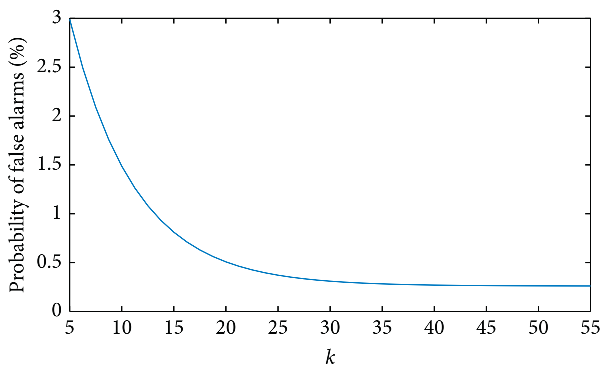

Figure 5: The relationship curve between the number of judgment matrices k and the false alarm rate of fire detection.

Table 4: The real value of fire probability corresponding to the three detection algorithms.

Fire detection algorithm	Fire probability (%)
Grey fuzzy neural network fusion method	30.56
Fuzzy logic fusion method	29.48
Online detection method	28.62

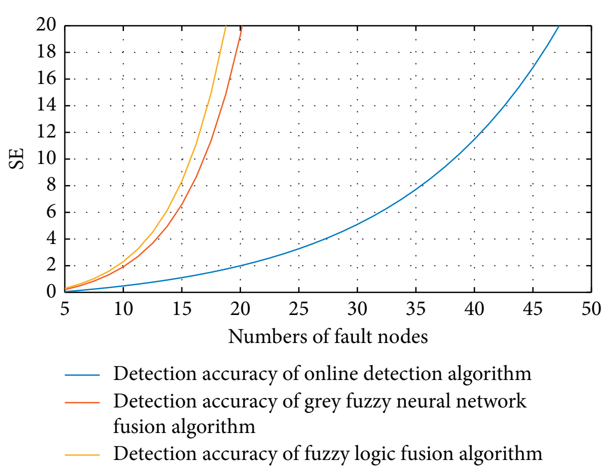

Figure 6: Comparison diagram of detection accuracy of three algorithms.

tolerance of the proposed online detection algorithm is much better.

5. Conclusions

In this paper, on the one hand, the online fire detection algorithm uses improved AHP and multivariable-weighted fusion algorithm to evaluate the fire event probability in cabin at each node. On the other hand, the fire probability evaluation values of all nodes are fused by adaptive-weighted fusion algorithm based on the augmented support matrix during online detection. Experiments show that the algorithm can complete fire detection and alarm within 10 s. Comparing the proposed method to other fire detection algorithms, it greatly reduces the time required for fire detection and alarm, effectively avoids the spread of fire, and makes subsequent fire-suppression work smoother to a certain extent. In the meanwhile, the false alarm rate of fire has been reduced to less than 0.5%, which plays an important role in promoting the development of civil aviation in the future in terms of safety and economy. At the same time, the simulation results show that the online detection algorithm has better fault tolerance than other fire detection algorithms in the WSN with faulty sensors.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

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References

[1] X. Jin, J. Du, and J. Bao, “Target tracking of a linear time invariant system under irregular sampling,” *International Journal of Advanced Robotic Systems*, vol. 9, no. 5, p. 219, 2012.

[2] X. Jin, X. Lian, T. Su, Y. Shi, and B. Miao, “Closed-Loop estimation for randomly sampled measurements in target tracking system,” *Mathematical Problems in Engineering*, vol. 2014, pp. 1–12, 2014.

[3] X. Jin, C. Dou, T. Su, X. Lian, and Y. Shi, “Parallel irregular fusion estimation based on nonlinear filter for indoor RFID tracking system,” *International Journal of Distributed Sensor Networks*, vol. 2016, no. 8, pp. 1–11, 2016.

[4] Y. Liang and W. Tian, “Multi-sensor fusion approach for fire alarm using bp neural network,” 2016.

[5] R. Wang, Y. Li, H. Sun, and Z. Chen, “Analyses of integrated aircraft cabin contaminant monitoring network based on Kalman consensus filter,” *ISA Transactions*, vol. 71, pp. 112–120, 2017.

[6] R. Wang, X. Wang, H. Sun, Y. Huang, and Z. Chen, “Analysis of estimator and energy consumption with multiple faults over the distributed integrated WSN,” *International Journal of Modelling, Identification and Control*, vol. 32, no. 2, pp. 154–168, 2019.

[7] S. Liu, X. Luo, W. Yao et al., “Aspirating fire detection system with high sensitivity and multi-parameter,” 2014.

[8] R. Sowah, K. O. Ampadu, A. R. Ofoli, K. Koumadi, G. A. Mills, and J. Nortey, “A fire-detection and control system in automobiles: implementing a design that uses fuzzy logic to anticipate and respond,” *IEEE Industry Applications Magazine*, vol. 25, no. 2, pp. 57–67, 2019.

[9] S. Duan, K. Yang, D. Mao, and J. Ren, "Fuzzy evidence theory-based algorithm in application of fire detection," *Computer Engineering and Applications*, vol. 53, no. 5, pp. 231–235, 2017.

[10] M. Yang, Y. Geng, K. Yu, X. Li, and S. Zhang, "BP neural network data fusion algorithm optimized based on adaptive fuzzy particle swarm optimization," 2018.

[11] K. Lamamra, A. Allam, and H. Afiane, "Artificial neural networks for acquisition and processing of sensors data in a radiotherapy application," *International Journal of Simulation and Process Modelling*, vol. 13, no. 1, pp. 15–23, 2018.

[12] F. Yang, Y. Shen, X. Cui et al., "Voltage sag severity assessment based on multi-objective decision analytic hierarchy process," 2018.

[13] H. Sun, F. Qiao, Z. Wang, and L. Guo, "A two-level identification model for selecting the coordination strategy for the urban arterial road based on fuzzy logic," *International Journal of Simulation and Process Modelling*, vol. 14, no. 6, pp. 478–487, 2019.

[14] W. Gao and K. Hong, "The portfolio balanced risk index model and analysis of examples of large-scale infrastructure project," *Complexity*, vol. 2017, pp. 1–13, 2017.

[15] W. Li, Y. Ye, N. Hu, X. Wang, and Q. Wang, "Real-time warning and risk assessment of tailings dam disaster status based on dynamic hierarchy-grey relation analysis," *Complexity*, vol. 2019, no. 9, pp. 1–14, 2019.

[16] M. Yu, X. Zhao, and Z. Xu, "Survey on using dependencies to improve data consistency," *Journal of Computer Applications*, vol. 38, no. 2, pp. 72–76, 2018.

[17] J. Yang, F. Gong, and Y. Ma, "A multi-sensors data fusion method based on the augmented support degree," 2010.

[18] S. Hu and J. Liu, "Application of fuzzy comprehensive evaluation method in product design scheme decision," *Journal of Machine Design*, vol. 37, no. 1, pp. 135–139, 2020.

[19] C. Ai and F. Feng, "A supplement to saaty's consistency theory of judgment matrix in the analytic hierarchy process," 2017.

[20] Q. Tian, C. Huang, H. Yu, Y. Du, and X. Zhou, "Approach for determining weight of resource allocation in coupled task set based on AHP," *Computer Engineering and Applications*, vol. 54, no. 21, pp. 25–30, 2018.

[21] H. Xu, P. He, W. Hsu, Y. Lee, and C. Ho, "Establishment of assessment indexes for intelligent elderly residential space by analytic hierarchy process," *Healthcare and Sustainability (ECBIOS)*, vol. 2019, pp. 69–72, 2019.

[22] W. Dong, J. Fu, Z. Jie, and J. Wang, "Study on operation evaluation of charging and discharging network based on improved analytic hierarchy process and fuzzy synthetic evaluation," 2018.

[23] Y. Liu, X. Yan, C.-A. Zhang, and W. Liu, "An ensemble convolutional neural networks for bearing fault diagnosis using multi-sensor data," *Sensors*, vol. 19, no. 23, p. 5300, 2019.

[24] L. Zheng, D. W. H. Cai, and C. W. Tan, "Max-min fairness rate control in wireless networks: optimality and algorithms by perron-frobenius theory," *IEEE Transactions on Mobile Computing*, vol. 17, no. 1, pp. 127–140, 2018.

[25] S. Zeng, X. Tong, and P. Shen, "Design of fire detection system based on wireless multi-sensor information fusion," *Journal of Hubei Polytechnic University*, vol. 35, no. 6, pp. 23–27, 2019.

[26] O. Giandi and R. Sarno, "Prototype of fire symptom detection system," 2018.