

Retraction

Retracted: The Application of Multisensor Information Fusion Technology in Environmental Restoration

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.


The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Yu, Y. Ye, W. Guo, S. Chen, and H. Zhang, "The Application of Multisensor Information Fusion Technology in Environmental Restoration," *Journal of Sensors*, vol. 2022, Article ID 9514361, 10 pages, 2022.

Research Article

The Application of Multisensor Information Fusion Technology in Environmental Restoration

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Multisensor information fusion technology is an advanced processing method that is different from classical data processing technology. Capability and operational accuracy, in order to make an effective comprehensive evaluation of environmental quality, the environmental monitoring system built by NB-IoT technology and sensor technology is used to conduct multisensor data fusion research on the collected environmental factors such as temperature, humidity, formaldehyde, PM2.5, and TVOC. At the same time, the two-level parallel fusion method is adopted to evaluate the environmental quality. Before data fusion, median filtering is used to eliminate abnormal data. Then, the Kalman filter algorithm is used to fuse multiple sets of similar sensors to obtain the best value of it. Finally, the fuzzy comprehensive evaluation method is used to fuse the different types of sensors at the decision-making level, in which the weight value is determined by the entropy method and the membership function is Gaussian. The different environment scenarios are tested by using the above algorithms, and the simulation results show that multisensor data fusion can obtain more abundant and effective environmental information, overcome the simplicity and limitation of single-factor sensor for environmental quality assessment, and improve the reliability and accuracy of the overall environmental quality assessment.

1. Introduction

With the rapid development of the global economy, China's economy has grown exponentially since the reform and opening up more than 40 years ago [1]. At the same time, behind the economic growth, China's environmental pollution problem is also "complimenting each other," and it is becoming more and more serious [2]. The main cause of environmental pollution is that the atmosphere contains a large amount of harmful substances [3]. In order to better realize the ecological sustainable development of the country, it is necessary to use advanced monitoring tools and environmental monitoring technologies in the process of monitoring, preventing, and governing the environment [4]. Therefore, in view of the current environmental pollution problem, it is urgent to

increase the monitoring of the environment and actively develop the monitoring technology of the environment [5]. With the rapid development of the Internet of Things technology, environmental monitoring is also bred. Embed advanced Internet of Things technology in environmental monitoring, and use multisensor fusion technology to organize and analyze comprehensive and accurate data collected by various sensors. The purpose is to accurately find problems in the current environment and timely prevention and control to improve environmental monitoring quality and monitoring efficiency [6]. At present, western developed countries such as the United States and the United Kingdom already have relatively complete environmental monitoring systems [7]. The United States launched environmental satellites in the 1980s to determine the state of global environmental quality [8]. Japan

establishes automated ambient air monitoring bureau to monitor regional air quality. Our country launched two environmental and disaster monitoring satellites in 2008. The airborne atmospheric and water environment pollution monitoring system developed by Anhui Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, realizes regional atmospheric environment monitoring. In the literature [9], the adaptive weighted fusion technology is used to monitor the soil environment. In the literature [10], the adaptive weighting algorithm and fuzzy neural network algorithm are used to monitor the environment. In [11], the weighted least squares method is used for multisensor fusion. Reference [12] uses the second-order adaptive weight particle filter method for multisensor information fusion. Reference [13] uses Bayesian method for data fusion. The soil and groundwater pollution situation in my country is severe. Only in the eastern plains and coastal areas, there are hundreds of thousands of potential pollution sites, many of which are organic pollution sites, especially organic solvent pollution such as chlorinated hydrocarbons and aromatic hydrocarbons.

The basic principle of multisensor information fusion (MSIF) technology is like the brain processing the information obtained by all sensing organs of the human body [14]. Unify and rationally utilize the capabilities of each sensor, reasonably allocate the computing units of each sensor, and comprehensively judge the validity and accuracy of the information [15]. The implementation of MSIF requires the installation of several similar or completely complementary sensors in multiple parts of the smart device to obtain single and incomplete information and then use information fusion algorithms to find possible potential connections among a large amount of data from different sensors [16]. Remove redundant information and form a complete system environment for accurate understanding [17]. Because of its unique advantages, it is widely used in the military field, economic field, robot intelligence field, medical field, etc. The method of information fusion is the most important part of multisensor information fusion [18, 19]. Due to the complexity and diversity of its application, the research content of information fusion is extremely rich, involving many basic theories, and the commonly used algorithm is Kalman filter, parameter template method, Bayesian inference, adaptive neural network, etc. The development of sensor technology has been relatively mature, and there are suitable sensor types for use in different environments, different types of data, and applications with different functions [20]. Most of the data acquired by the sensor is used to obtain the state of the system or to perceive the surrounding environment [21]. Nowadays, the mainstream environmental perception methods can be roughly divided into two types: image-based information perception and wave-based information perception according to the working principle of the sensor [22, 23]. On the basis of the first-level Kalman filter, in order to effectively and reasonably evaluate a variety of environmental factors, the fuzzy comprehensive evaluation method can avoid the limitation of a single sensor to evaluate the environmental quality.

In the multisensor information fusion technology, if all the sensors are configured with the standard time stamp, the coordinate systems of all sensors are transformed into absolute or relative coordinate systems. In order to get an accurate description of the environment, while using multiple sensors to work together, it is also necessary to transmit the collected information to the data fusion center [24]. After a series of data processing, a complete description can be obtained. Based on the general structure, multisensor information fusion can also be divided into three categories: centralized, distributed, and hybrid. Centralized fusion is to transmit the measurement information obtained by all sensors directly to the central processing unit for unified processing [25]. In this structure, if all sensors are configured with standard timestamps, the coordinate systems of all sensors are transformed into absolute or relative coordinate systems [26]. Based on the general structure, multisensor information fusion can also be divided into three categories: centralized, distributed, and hybrid. Centralized fusion is to transmit the measurement information obtained by all sensors directly to the central processing unit for unified processing. Rich raw information that can provide the most accurate information that other fusion layers cannot. The amount of sensor data that needs to be processed is huge, the processing cost is high, the time is long, and the real-time performance is poor. Raw data is easily polluted by noise.

In the past, the fusion of large amounts of data was mostly realized by offline processing after real-time storage. However, with the development of sensor technology, the measurement accuracy of sensors is getting higher. The environmental monitoring system designed in this paper combines Narrowband Internet of Things (NB-IoT) technology and two-level parallel fusion technology to evaluate environmental quality [27]. Before the first-level fusion, the median filter algorithm is used to remove abnormal data to improve the data accuracy, and then, the Kalman filter algorithm is used to perform the first-level fusion of the five environmental factors to provide accurate and effective data for the second-level fusion [28]. The second-level fusion uses the fuzzy comprehensive evaluation method to fuse the various sensor values after the fusion of the previous level at the decision-making level, which avoids the singleness of environmental quality monitoring and overcomes the shortcomings of inaccurate environmental evaluation by a single factor [29]. The multisensor fusion algorithm improves the accuracy of the Narrowband Internet of Things- (NB-IoT-) based environmental monitoring system and provides convenience for users to view environmental monitoring data on the platform in real time and understand the environmental conditions.

2. NB-IoT's Environmental Monitoring System Architecture

This paper uses STM32F103C8T6 as the main control chip and obtains the data collected by various sensor modules through the combination of software and hardware. Use NB-IoT technology to send a variety of sensor data to the

cloud platform, view monitoring data in real time through the cloud platform, extract data, and perform data fusion processing. Although information fusion technology has been gradually developed since the early 1970s, there is no universal algorithm that can satisfy all usage scenarios. According to the concept of algorithm, it is mainly divided into three categories: physical model, parameter-based model, and cognitive-based model. The rapid development of Internet of Things technology has brought vitality to environmental monitoring and injected new vitality. The environmental monitoring system designed by using the Internet of Things technology can effectively improve the real-time performance and effectiveness of the monitoring system, share the collected data and information with each other, and provide a strong guarantee for environmental monitoring [30]. Compress the provided raw data to reduce interference noise, which is more suitable for real-time processing. Feature vector combination classification is performed on related data before fusion. The entire environmental monitoring data is provided by the temperature and humidity sensor DHT22, the formaldehyde sensor ZE08-CH₂O, the dust (PM_{2.5}) sensor ZPH01, and the total volatile organic compound (TVOC) sensor KQM2008A, and the data is uploaded to China Mobile (OneNET) using NB-IoT technology, in which the hardware structure of the environmental monitoring system is shown in Figure 1.

The temperature and humidity sensor DHT22 uses single-bus communication to transmit 40-bit data including temperature and humidity integers, decimals, and parity. Compared with DHT11, the advantage is that the collection volume can reach decimal places, the response speed is fast, and the anti-interference ability is strong. It also applies special digital module acquisition technology to ensure its reliability and stability. Design verification functions in the software program to ensure the accuracy of the output data. Single-dimensional data fusion cannot meet applications in complex scenarios, and it also limits the capabilities of the system. The future development of multisensor data fusion technology should develop towards multitype sensors, multidimensional fusion, and multistrategy fusion to adapt to simple to complex application scenarios and improve system robustness and stability.

The formaldehyde sensor ZE08-CH₂O is designed with electrochemical detection technology and built-in temperature compensation circuit with high stability and resolution less than 0.012 5 mg/m³. Adopt Universal Asynchronous Receiver Transmitter (UART) communication protocol, also output accurate data according to the check function. Dust sensor ZPH01 has extremely high sensitivity and long-term stability, among which the minimum particle output capacity of dust is 1 μm, the communication method is UART and equipped with calibration value. Total volatile organic compound (TVOC) sensor KQM2008A integrates 12-bit high-precision digital-to-analog conversion. The module uses Fourier transform and separation algorithm to suppress drift and improve accuracy and outputs accurate data through UART. Finally, the collected data is used multisensor fusion technology to evaluate the pros and cons of monitoring the environmental quality of the entire system. Multisensor

fusion is a technology for data information calibration, correlation, identification, and estimation. The degree of information processing is divided into three levels from low to high: data-level fusion, feature-level fusion, and decision-level fusion. In order to better use the multisensor fusion technology, it is necessary to determine its fusion structure, and the basic fusion structure is divided into three types, which are serial fusion, parallel fusion, and hybrid fusion [31]. According to the type of fusion structure, combined with the way the environmental monitoring system designed in this paper collects data, the multisensor fusion algorithm model of the whole system is designed as a two-stage parallel fusion, and the fusion model is shown in Figure 2.

3. Homogeneous Sensor Fusion Algorithm

In order to make the overall fusion algorithm evaluate the environmental quality more accurately and meet the standards of multisensor data fusion technology, this paper will set up 5 environmental monitoring subsystems to obtain environmental data including temperature, humidity, formaldehyde, PM_{2.5}, and TVOC, so before the first-level fusion process, a median filter function is added to each type of sensor. The purpose is to make each sensor improve the accuracy of the collected data on the premise of obtaining effective values and effectively overcome the fluctuation interference caused by accidental factors. Simple and intuitive weighted average algorithm is a way to directly manipulate the data source provided by the sensor and use the weighted average as the fusion value. The difference between data processing methods and classical methods in multisensor data fusion can be manifested in complex forms. And different information levels have different complex forms. Bayesian estimation is also a low-level data fusion method, which mainly combines static data collected by sensors according to the principle of probability. The Kalman filter itself is very dependent on the accuracy of its system model. If the state of the system and the measurement model are sufficiently accurate, then Kalman filtering can recursively provide the best estimate of the combined data in a statistical sense. While Kalman filtering is mainly used to fuse low-level real-time dynamic multisensor redundant data, this method uses the statistical features of the measurement model to recurse and determine the best fusion and data estimation in the statistical sense. Therefore, the first-level fusion will use the Kalman filter algorithm. Compared with the original data, the amount of information of the preprocessed data will be greatly reduced. The advantage of this is that it can effectively reduce the bandwidth requirements for information transmission. At the same time, the computational load of the fusion unit will be reduced so that more complex algorithms can be deployed without losing too much time. Kalman filter, also known as optimal autoregressive data processing algorithm, is a recursive estimation algorithm based on linear minimum variance of state variables. If the system has a linear dynamic model and the error between the system and the sensor conforms to a Gaussian white noise model, then Kalman filtering will provide the only statistically optimal estimate for the fused data. Due

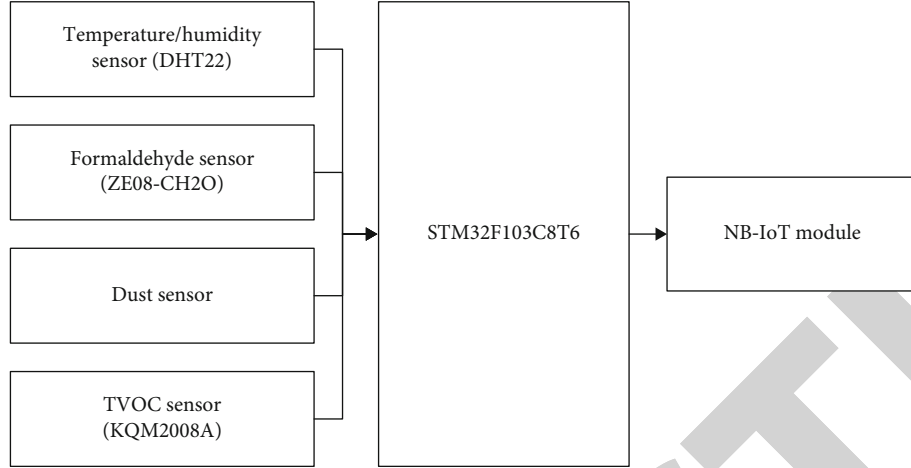


FIGURE 1: Hardware structure diagram of the environmental monitoring system.

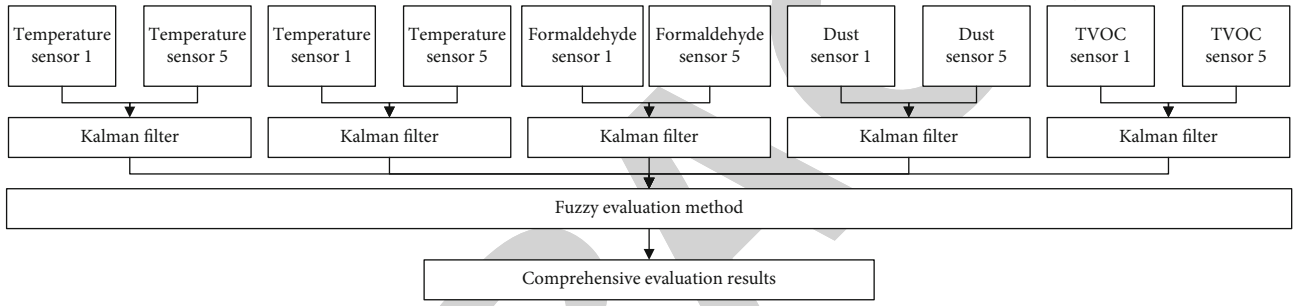


FIGURE 2: Two-stage parallel fusion model.

to the differences in the gas sensor itself and its environment, the noise frequency also changes, so when the frequency of some noise overlaps with the bandwidth of the desired signal, the classical filter for distinguishing the spectral response does not apply. In order to reduce the random measurement error caused by the quality of the sensor equipment and the aging of the components in the process of collecting data of the homogeneous sensor and reduce the noise pollution of the sensor caused by external factors such as temperature, humidity, air pressure, wind speed, and light changes, Mann filtering can well control the interference of noise on real data and provide statistically accurate and effective data for the second-level data fusion.

The main steps of the Kalman filter algorithm are as follows.

- (1) The equation for the predicted value is as follows:

$$\mathbf{P}(k|k-1) = \mathbf{TP}(k-1|k-1) + \mathbf{BU}(k). \quad (1)$$

In the formula, $\mathbf{P}(k|k-1)$ is the result predicted by the previous state, \mathbf{T} is the state transition matrix, $\mathbf{P}(k-1|k-1)$ is the optimal result of the previous state, \mathbf{B} is the input control term matrix, and $\mathbf{U}(k)$ is the current state control quantity.

- (2) The covariance matrix equation for the error between the predicted value and the true value is as follows:

$$\mathbf{C}(k|k-1) = \mathbf{TC}(k-1|k-1)T^T + \mathbf{N}. \quad (2)$$

In the formula, $\mathbf{C}(k|k-1)$ is the covariance of the prediction result of the previous state, $\mathbf{TC}(k-1|k-1)$ is the covariance of the optimal result of the previous state, and \mathbf{N} is the noise covariance.

- (3) The Kalman gain equation is as follows:

$$\mathbf{G}(k) = \frac{\mathbf{C}(k|k-1)\mathbf{M}^T}{\mathbf{MC}(k|k-1)\mathbf{M}^T + \mathbf{E}}, \quad (3)$$

where $\mathbf{G}(k)$ is the Kalman gain, \mathbf{M} is the measurement matrix, and \mathbf{E} is the measurement noise covariance.

- (4) The filter estimation equation is as follows:

$$\mathbf{P}(k|k) = \mathbf{P}(k|k-1) + \mathbf{G}(k) \mathbf{Z}(k) - \mathbf{MP}(k|k-1). \quad (4)$$

In the formula, $\mathbf{P}(k|k)$ is the current optimal estimated value, and $\mathbf{Z}(k)$ is the measured value of the sensor.

(5) The covariance matrix update equation is as follows:

$$\mathbf{C}(k|k) = [-\mathbf{G}(k)\mathbf{M}(k)]\mathbf{C}(k|k-1), \quad (5)$$

where $\mathbf{C}(k|k)$ is the covariance of the current optimal estimation result and I is the identity matrix.

According to the above equation, the core idea of summarizing the Kalman filter algorithm is to calculate the current optimal value based on the current measurement value of the sensor and the predicted value and error at the previous moment.

Due to the large number of heterogeneous sensors in this system, only 20 sets of data collected by five sets of temperature sensors are shown for first-level fusion. The temperature values collected by the temperature sensor are shown in Table 1.

By performing Kalman filtering on the collected 20 sets of data, the first-level fusion result of the temperature sensor is output. The Kalman filtering simulation result of the temperature sensor value is shown in Figure 3, and the error comparison result is shown in Figure 4.

It can be seen from the filtering results in Figure 4 that the temperature sensor value after the first stage fusion is 28.06°C, and the average value of the 20 sets of data is 28.07°C. The standard value of 28°C is used to measure the accuracy of the Kalman filter algorithm and the average algorithm, and the superiority and accuracy of the Kalman filter algorithm are compared through the final results. The error result comparison chart in Figure 5 also shows the ability of the Kalman filter algorithm to process data. The error after Kalman filter is smaller than the measured value and only 0.21%, which indicates that the Kalman filter algorithm satisfies the first requirements for data processing in the process of level fusion.

4. Heterogeneous Sensor Fusion Algorithms

The basic principle is to first determine the set of factors for evaluating environmental quality; then, determine the weight of each factor and its membership vector to obtain a fuzzy evaluation matrix. Finally, fuzzy operation is performed on the fuzzy evaluation matrix and factor weight vector and normalized, and the fuzzy comprehensive evaluation result is obtained. For all kinds of environmental data monitored, people are not interested in their values; what they care about is the comfort brought by the quality of the environment. Therefore, on the basis of the first-level Kalman filter, in order to effectively and reasonably evaluate a variety of environmental factors, the fuzzy comprehensive evaluation method can avoid the limitation of a single sensor to evaluate the environmental quality. The fuzzy comprehensive evaluation method transforms qualitative evaluation into quantitative evaluation through the theory of fuzzy

TABLE 1: Temperature statistics.

Sample number	Temperature	Sample number	Temperature
1	28.1	11	27.8
2	28.1	12	27.9
3	28.2	13	28.0
4	27.9	14	28.1
5	28.0	15	28.1
6	28.0	16	28.1
7	28.2	17	28.2
8	28.3	18	28.3
9	28.1	19	28.0
10	28.0	20	28.0

mathematics membership degree, that is, comprehensive evaluation of things or objects affected by various factors.

4.1. Determine the Weight of Each Factor. For the environmental monitoring system indicators in this paper, the weights refer to the importance of temperature, humidity, formaldehyde content, PM2.5 content, and TVOC content for environmental quality evaluation. In the fuzzy comprehensive evaluation, the weight has a great influence on the final evaluation result. Different weights sometimes lead to completely different conclusions. Therefore, choosing an appropriate method to determine the weight of each factor is a key step in the environmental evaluation system. Generally, the Analytic Hierarchy Process (AHP) is chosen to determine the weights, but this algorithm is biased towards human subjective factors and mainly includes personal qualitative judgments, which makes the weight distribution poor. The entropy method refers to a mathematical method used to judge the degree of dispersion of a certain index. In information theory, entropy is the quantification of the degree of disorder in the system. It can measure the amount of information provided by the original data, the amount of information provided by each indicator to determine the indicator weight. The smaller the information entropy, the lower the disorder degree of the information, the greater the utility value of the information in the comprehensive evaluation, and the greater the weight of the index. That is, the entropy value method can profoundly reflect the utility value of the entropy value of the index information, overcome the subjective defects of the AHP, and improve the reliability and accuracy of the index weight. Finally, the entropy value method is used to determine the weight. According to the algorithm steps of the entropy method, a mathematical model is established through MATLAB, and the data in Table 2 is substituted into the program to obtain the relevant weights $A = \{a_1, a_2, a_3, a_4, a_5\}$, where the weight values are arranged in the order of temperature, humidity, formaldehyde, PM2.5, and TVOC. The specific algorithm process is as follows.

- (1) First, the data in Table 2 is represented in the form of a matrix

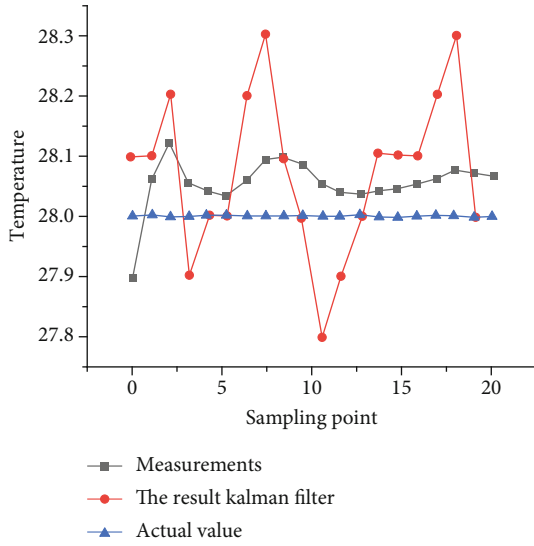


FIGURE 3: Kalman filter of temperature sensor.

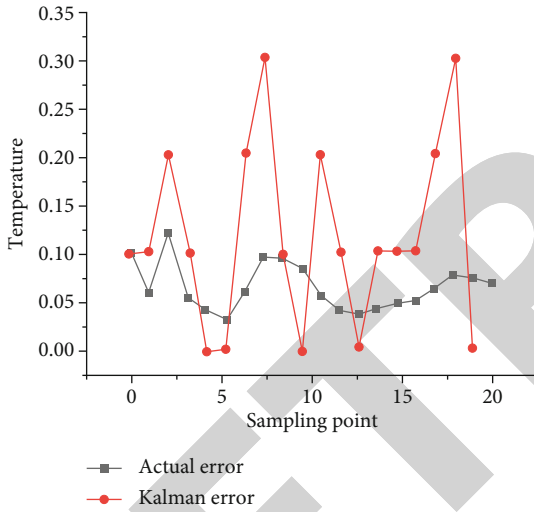


FIGURE 4: Error comparison.

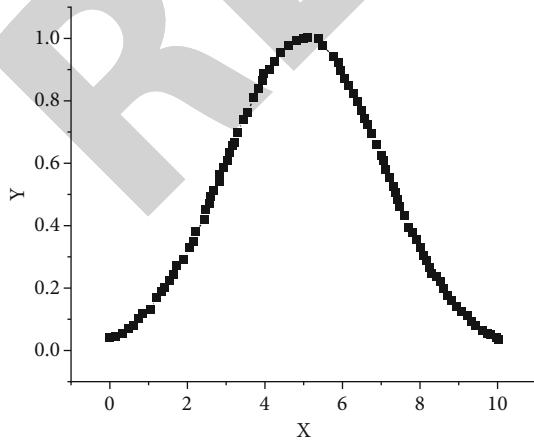


FIGURE 5: Gaussian membership function.

(2) The data are normalized according to the formula

$$x'_{ij} = \frac{x_{ij} - \min \{x_{ij}, \dots, x_{nj}\}}{\max \{x_{1j}, \dots, x_{nj}\} - \min \{x_{1j}, \dots, x_{nj}\}} \quad n = 1 \dots 5. \quad (6)$$

(3) Calculate the proportion of normalized data

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}}, \quad i = 1, \dots, n, j = 1, \dots, m. \quad (7)$$

(4) Calculate the entropy value for each factor

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad k = \frac{1}{\ln 5}. \quad (8)$$

(5) Calculate the information entropy redundancy for each factor

$$d_j = 1 - e_j. \quad (9)$$

(6) Calculate the weight of each factor

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad m = 1, \dots, 5. \quad (10)$$

4.2. Determining Fuzzy Relationship Matrix. The key to determine the fuzzy relationship matrix R is to determine the membership function and calculate the membership degree of each element in the comment set through the membership function. According to the environmental indicators in this paper, the Gaussian membership function is selected for solving, because each sensor value conforms to the normal distribution under each evaluation set. Its expression is as follows:

$$y = e^{-[x-b]/\sigma]^2} \quad -\infty < x < +\infty. \quad (11)$$

In the formula, x is the value of each sensor after the first-level fusion, b is the standard value of the evaluation set V corresponding to each sensor, and σ is the standard deviation of the evaluation set corresponding to each sensor.

The simulation of the Gaussian membership function model is shown in Figure 5, where the standard deviation $\sigma = 2$ and $b = 5$.

TABLE 2: Environmental monitoring values.

Surroundings	Temperature (°C)	Humidity (%RH)	Formaldehyde (mg/m ³)	PM2.5 (μg/m ³)	TVOC (mg/m ³)
1	28.1	58.5	0.021 2	70.2	0.02
2	28.1	58.6	0.022 5	70.0	0.03
3	28.2	58.2	0.021 2	69.8	0.03
4	27.9	58.5	0.023 7	70.0	0.02
5	28.0	58.3	0.021 2	70.2	0.02
6	28.0	58.4	0.021 2	70.2	0.02
7	28.2	58.6	0.022 5	70.1	0.03
8	28.3	58.3	0.021 2	70.0	0.03
9	28.1	58.6	0.023 7	70.3	0.03
10	28.0	58.5	0.022 5	70.1	0.03
11	27.8	58.5	0.020 0	69.9	0.04
12	27.9	58.4	0.022 5	69.9	0.03
13	28.0	58.5	0.022 5	70.0	0.02
14	28.1	58.6	0.021 2	70.0	0.02
15	28.1	58.5	0.021 2	70.1	0.02
16	28.1	58.5	0.023 7	70.0	0.03
17	28.2	58.3	0.022 5	70.1	0.03
18	28.3	58.4	0.022 5	69.9	0.03
19	28.0	58.5	0.021 2	70.0	0.03
20	28.0	58.5	0.021 2	70.0	0.03

5. Analysis and Verification of Data Fusion Algorithms

The collection site was selected on the first floor of the Fok Ying Tung Building of Zhongkai University of Agriculture and Engineering. The five environmental monitoring systems were placed separately, and the data was collected every 15 minutes, 4 times for a total of 20 groups, and the data is drawn in Table 3.

According to the steps of the above multisensor fusion algorithm, the data of each homogeneous sensor is first fused, and the result after Kalman filtering is {temperature: 28.06°C, humidity: 58.45%RH, formaldehyde: 0.021 mg/m³, PM2.5: 70.02 μg/m³, TVOC: 0.025 mg/m³}.

The second-level fusion determines the factor set $U = \{\text{temperature, humidity, formaldehyde, PM2.5, TVOC}\}$ and the comment set $V = \{\text{good, better, fair, poor, poor}\}$ according to the fuzzy comprehensive evaluation algorithm steps. Then, determine the weight of each factor, and calculate $A = \{0.1117, 0.1021, 0.1239, 0.1211, 0.5412\}$. Then, the fuzzy relation matrix is determined according to the Gaussian membership function of each sensor.

In order to better verify the rationality and effectiveness of the system fusion algorithm, the environmental conditions of the road near Zhongkai University of Agriculture and Engineering and the construction unit of a real estate building were tested respectively. First test the environmental conditions of road crossings near Zhongkai University of Agriculture and Engineering. Kalman filter result {temperature: 19.83°C, humidity: 52.795%RH, formaldehyde: 0.048 0 mg/m³, PM2.5: 92.82 μg/m³, TVOC: 0.047 mg/m³}. Due to the seasonal changes of the collected data, the standard

values of the temperature index evaluation set are adjusted accordingly. Calculate the standard deviation of the standard value of the temperature index evaluation set $\sigma = 5.38$. According to formula (11), the Gaussian membership function of the temperature index is obtained:

$$r_{ij} = e^{-[19.83-b_{ij}]^2/5.38^2}, \quad -\infty < x < +\infty. \quad (12)$$

Using the collected monitoring data, the fusion algorithm is used to measure the weight vector A of each environmental factor of the road near Zhongkai University of Agriculture and Engineering, and the fuzzy relation matrix R is as follows.

$$R = \begin{bmatrix} 0.1533 & 0.3281 & 0.3856 & 0.1193 & 0.0137 \\ 0.2343 & 0.4097 & 0.2559 & 0.0970 & 0.0031 \\ 0.2621 & 0.4422 & 0.2201 & 0.0649 & 0.0107 \\ 0.1824 & 0.3197 & 0.3095 & 0.1849 & 0.0035 \\ 0.7673 & 0.2111 & 0.0209 & 0.0007 & 0.0000 \end{bmatrix}. \quad (13)$$

According to formula (12), the fuzzy comprehensive evaluation result vector $C = \{0.3067, 0.3464, 0.2483, 0.0914, 0.0071\}$ is calculated. "Good" accounted for a relatively high proportion. Using the principle of maximum membership, the environmental quality of roads in this area is better. Compared to the environmental conditions in the area, the environmental quality of roads has declined. In order to

TABLE 3: Road monitoring data near Zhongkai University of Agriculture and Engineering.

Surroundings	Temperature (°C)	Humidity (%RH)	Formaldehyde (mg/m ³)	PM2.5 (μg/m ³)	TVOC (mg/m ³)
1	19.7	52.6	0.021 2	70.2	0.04
2	28.1	52.6	0.022 5	70.0	0.04
3	28.2	52.8	0.021 2	69.8	0.05
4	27.9	58.5	0.023 7	70.0	0.03
5	28.0	52.8	0.021 2	70.2	0.02
6	28.0	58.4	0.021 2	70.2	0.02
7	28.2	52.6	0.022 5	70.1	0.03
8	28.3	58.3	0.021 2	70.0	0.03
9	28.1	52.6	0.023 7	70.3	0.03
10	19.7	58.5	0.022 5	70.1	0.03
11	27.8	58.5	0.020 0	69.9	0.04
12	20.0	52.6	0.022 5	69.9	0.03
13	28.0	52.6	0.022 5	70.0	0.02
14	20.1	58.6	0.021 2	70.0	0.02
15	28.1	58.5	0.021 2	70.1	0.02
16	20.1	52.6	0.023 7	70.0	0.03
17	19.9	58.3	0.022 5	70.1	0.03
18	28.3	52.6	0.022 5	69.9	0.03
19	19.8	58.5	0.021 2	70.0	0.03
20	19.8	58.5	0.021 2	70.0	0.03

reflect the rationality and effectiveness of the algorithm in this paper, the monitoring data obtained from the provincial air quality real-time release system network are compared as shown in Figures 6–8, where Figure 6 represents the change of PM2.5 in 24 hours, Figure 7 represents the change in AQI within 24 hours, and Figure 8 represents the change in AQI within a week.

It can be seen from Figures 6–8 that the environmental indicators monitored by the provincial environmental monitoring center station are SO₂, NO₂, CO, O₃, PM₁₀, and PM_{2.5}. It uses AQI (Air Quality Index) to determine the environmental quality, which is divided into six levels. In this monitoring period, the environmental quality of the area is shown to be second-level good, and the environmental quality measured by the data fusion algorithm in this paper is good, which can well reflect the rationality and effectiveness of the system algorithm in this paper. In order to further improve the rationality and effectiveness of the fusion algorithm, a construction unit of a building near the area was tested, where Kalman filter result {temperature: 21.83°C, humidity: 58.922% RH, formaldehyde: 0.0618 mg/m³, PM_{2.5}: 180.95 μg/m³, TVOC: 0.0795 mg/m³}. According to the data fusion algorithm in this paper, the weight vector $A = \{0.3799, 0.0689, 0.1889, 0.1523, 0.2100\}$ and the fuzzy relation matrix R as follows. According to formula (12), the fuzzy comprehensive evaluation result vector $C = \{0.2934, 0.2981, 0.2287, 0.1352, 0.0446\}$ is calculated; using the principle of maximum membership degree, it can be seen that the region environmental quality is better. Through the analysis and verification of the above three sets of experimental data, the reliability of the environmental

quality detection results obtained by applying the multisensor fusion model in this paper is relatively high.

6. Conclusions

In this paper, the environmental monitoring system designed by NB-IoT technology and multisensor technology is used to collect data such as temperature, humidity, formaldehyde concentration, PM_{2.5} concentration, and TVOC concentration through the STM32F103C8T6 microcontroller. Firstly, median filtering is performed on the data collected by various sensors before the first-level data fusion, in order to eliminate abnormal data caused by external factors and provide accurate data for Kalman filtering. Kalman filtering is performed on the data of homogeneous sensors to realize the first-level data fusion, and the purpose is to provide effective data in statistical significance for the second-level fusion. Among them, the error brought by the Kalman filter is relatively small. Then, the fuzzy comprehensive evaluation method is used to fuse the data of heterogeneous sensors at the second level. The weight of each index is determined by the entropy method, which can solve the error caused by human factors, and the membership degree is solved by the Gaussian membership function. The characteristics of the normal distribution of the values are finally obtained, and the comprehensive evaluation results of the environmental quality are finally obtained. The research results of this paper will provide a useful reference for environmental monitoring-related technologies. Intelligence is the trend and trend of industrial development in modern society. Many fields and disciplines involved in multisensor

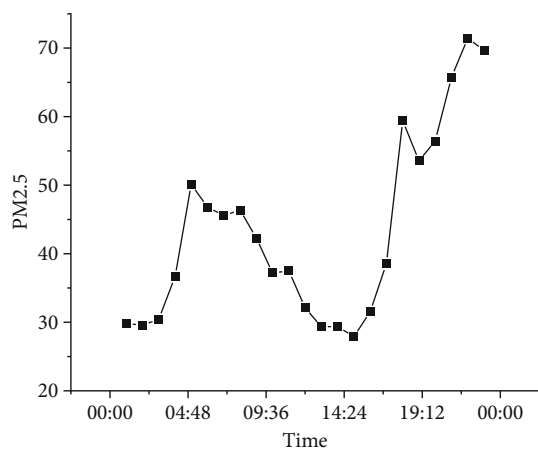


FIGURE 6: PM2.5 change in 24 hours.

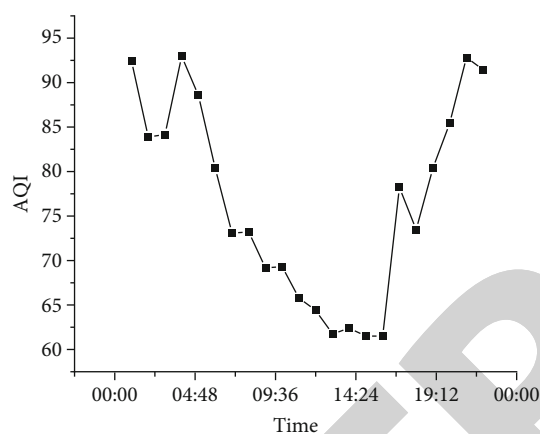


FIGURE 7: Changes in AQI within 24 hours.

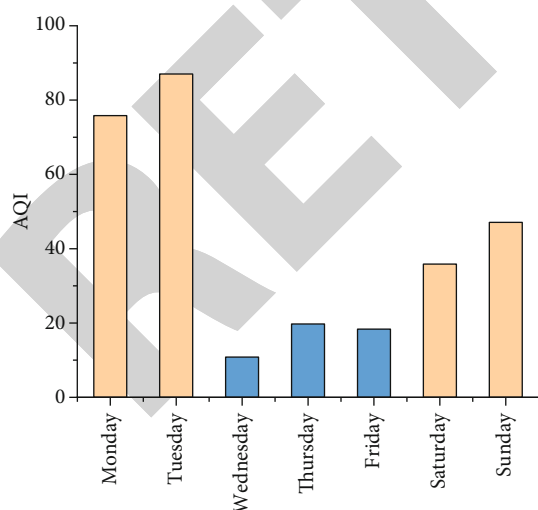


FIGURE 8: Changes in AQI within a week.

data fusion technology are closely related to artificial intelligence. In the future, multisensor data fusion technology will also develop towards intelligence.

Multisensor fusion technology is a multidisciplinary advanced technology, and its development direction needs

to meet the needs of current industrial development and social development, to meet people's daily work, life, production needs. Whether it is used in military, civilian, or scientific research, it can exert practical advantages. Multisensor data fusion technology needs to make it possible to achieve high-speed online fusion on the premise of ensuring robustness and accuracy. In the future, multisensor data fusion technology will still require hardware technology. With the support of continuous optimization algorithm calculation speed, improve the ability of high-speed online fusion.

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.

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