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Temperature Monitoring System For Plant Factory Based On Multi-Sensor Data Fusion

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Abstract

For the problem of low accuracy of temperature monitoring system, this paper proposed a multi-sensor data fusion algorithm applied to plant factory temperature monitoring system. First, Dixon criterion was used to eliminate the gross error in the measurement data, then the temperature data fusion value and variance in each group were obtained through patch estimation fusion method based on the average value, and finally the adaptive weighted fusion was conducted on each group of sensor data in accordance with the optimal distribution principle of the weight to obtain accurate temperature value. Results showed that the algorithm had higher accuracy and smaller error than the traditional average method.

1 Introduction

Plant factory has drawn wide attention from the governments around the world and international known enterprises in recent years, and plant factory is an efficient production method which can use intelligent automatic control technology to obtain plant products (taste, nutrition, green, health, etc.) that people need at minimal cost (space, time, material, water and electricity, economic cost, etc.) according to the growth environment requirements of agricultural crops. Plant factory controls the environmental factors of plant growth through the intelligent automatic control system in a closed environment, including light, temperature, humidity, CO2 concentration and nutrient solution [1]. The monitoring of the temperature in the plant factory plays an important role in increasing control system accuracy, and saving energy consumption. However, the sensor is easy to be interfered by external factors and is influenced by its accuracy[2], so the test result can't reflect the real state. Therefore, it is difficult to achieve the requirement of precise collection of temperature information by using the traditional single sensor monitoring technology, and the multi-sensor cooperative work must be adopted to complete the monitoring task. Choosing the appropriate multi-sensor data fusion method to improve the accuracy of monitoring data has become one of the key tasks of the plant factor environment monitoring [3].

Many scholars at home and abroad did a lot of research of multi-sensor data fusion technology. The literature [4] adopted patch estimation fusion algorithm for miniature plant factory temperature and humidity monitoring system, which improved the sensor accuracy. The literature [3] proposed an improved batch estimation adaptive weighted fusion algorithm, which solved the problem of low accuracy of wireless multi-sensor monitoring data fusion in the greenhouse combined with the adaptive weighted fusion. The literature [5] proposed a hybrid data processing method, which adopted the adaptive weighted fusion algorithm to conduct the fusion processing on large amounts of humidity data in the greenhouse, to obtain more accurate humidity value. The literature [6] proposed an optimized bayesian estimation multi-sensor data fusion method, which combined the bayesian estimation with kalman filter to be used in wireless sensor network data fusion, effectively solving the uncertainty and inconsistency of data. This paper put forward a multi-sensor data fusion algorithm applied to plant factory temperature monitoring system. First, Dixon criterion was used to eliminate the gross error in the measurement data, then the temperature data fusion value and variance in each group were obtained through patch estimation fusion method based on the average value, and finally the adaptive weighted fusion was conducted on each group of sensor data in accordance with the optimal distribution principle of the weight to calculate the accurate temperature value in the plant factory.

2 Data fusion algorithm

2.1 Gross error handling

Gross error is the abnormal data with large error occurring by chance in the testing process, and is mainly caused by the misoperation of operators, external disturbance or experimental device damage[7]. Gross error reduces the credibility of the data and should be removed. The elimination method of gross error mainly includes Laiyite criterion, Lomnaofski norm, Grubbs criterion and Dixon criterion[8]. The first three discrimination technologies must find the standard deviation first, with great computational burden, while Dixon criterion can quickly judge gross errors with less computational burden by using the differential ratio method, so as to get reliable measurement data. Because the sensor is easy to be interfered by external factors and is influenced by its accuracy in the process of sensor data collection in the plant factory, it is inevitable that there will be gross errors. In order to eliminate the data with large error, and improve accuracy, this paper adopted Dixon criterion to process the measurement data.

Through the research of the distribution of the statistics $x_{(i)}$ of $x_1, x_2, \cdots, x_n$, Dixon found when x_i obeyed the normal distribution, $x_{(n)}$ statistics can be obtained as follows:

$$r_{ij} = \frac{x_{(n)} - x_{(n-i)}}{x_{(n)} - x_{(j+1)}} \quad 1 \le i \le 2, 0 \le j \le 2 \quad (1)$$

Select the significance α as 0.01 or 0.05, and get the critical values $f_0(n,\alpha)$ of the statistics. When the measured statistic r_{ij} was greater than the critical value, $x_{(n)}$ was thought to contain gross error.

The minimum value $x_{(1)}$ was tested with the same critical value, and that was:

$$r_{ij} = \frac{x_{(1)} - x_{(i+1)}}{x_{(1)} - x_{(n-j)}} \quad 1 \le i \le 2, 0 \le j \le 2 \quad (2)$$

In order to delete the gross error, Dixon thought: When $n \le 7$, the effect of using r_{10} was better; When $8 \le n \le 10$, the effect of using r_{11} was better; When $11 \le n \le 13$, the effect of using r_{21} was better; When $n \ge 14$, the effect of using r_{22} was better[9]; When $n = 8$ in the system, $f_0(n,\alpha)$ can be selected as shown in Table 1.

$f_0(n,\alpha)$	n					
	8	7	6	5	4	3
$\alpha = 0.01$	0.683	0.637	0.698	0.78	0.889	0.988
$\alpha = 0.05$	0.554	0.507	0.56	0.642	0.765	0.941

Table 1: Critical value of Dixon criterion

2.2 Data processing of patch estimation fusion method based on the average value

After the gross error of each group of sensor data was eliminated by Dixon criterion, the consistency measurement data was obtained, and then the data processing of patch estimation fusion method based on the average value was adopted to fuse several temperature data in each group into an accurate temperature value. The batch estimation theory was an algorithm to conduct the fusion processing of measured value of the same tested thing in different positions. Detailed introduction was as follows: 8 temperature sensors were placed in the tested typical positions of plant factory, the measured data was divided into 2 groups, respectively including $x_{11}, x_{12}, \cdots, x_{1m}$ and $x_{21}, x_{22}, \cdots, x_{2n}$, $m \le 4$, $n \le 4$ and the average values $\overline{X}_1$, $\overline{X}_2$ and standard deviation σ_1, σ_2 of two groups were:

$$\overline{X}_1 = \frac{1}{m}\sum_{i=1}^{m} x_{1i} \quad (3)$$

$$\overline{X}_2 = \frac{1}{n}\sum_{i=1}^{n} x_{2i} \quad (4)$$

$$\sigma_1 = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(x_{1i} - \overline{X}_1)^2} \quad (5)$$

$$\sigma_2 = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{2i} - \overline{X}_2)^2} \quad (6)$$

According to the research of literature , the batch estimation theory in the statistics was used to solve the fusion value X^+ and variance σ^+ of the measured data according to formulas (3), (4), (5) and (6):

$$X^+ = \frac{\partial_1^2 \overline{X}_2 + \partial_2^2 \overline{X}_1}{\partial_1^2 + \partial_2^2} \quad (7)$$

$$\sigma^+ = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2} \quad (8)$$

2.3 Multi-sensor adaptive weighted data fusion

Because the measured data in different groups had different weights, using the adaptive weighted data fusion algorithm can distinguish the measured data in each group. Under the optimal condition of the minimum total mean-square error, their corresponding weights were found in the adaptive form according to groups of data measured by the temperature sensor, and finally the fused data can be optimized [10].

Adaptive weighted fusion estimated value:

$$\hat{X} = \sum_{i=1}^{N} W_i X_i \quad (9)$$

$$\sum_{i=1}^{N} W_i = 1 \quad (10)$$

Where in,

W_i —— Weights of each group of fusion values

X_i ——Fusion value in each group

$\hat{X}$ ——Estimated value after weighted average

N ——Number of groups of measured data, N=3

So the total square deviation after fusion was:

$$\sigma^2 = \sum_{i=1}^{N} W_i^2 \sigma_i^2 \quad (11)$$

According to the theory of multivariate function solving extreme values, when the weighting factor was:

$$W_i = \frac{1}{\sigma_i^2 \sum_{i=1}^{N} \frac{1}{\sigma_i^2}} \quad (12)$$

the minimum σ^2 can be calculated, and

$$\sigma^2_{\min} = \frac{1}{\sum_{i=1}^{N} \sigma_i^2} 。$$

3 Test results and analysis

3.1 Test platform

Plant factory temperature monitoring system is mainly composed of multi-channel temperature acquisition module, controller, data storage module, and display screen. The digital temperature sensor DS18B20 was selected to realize the temperature data acquisition in the multi-channel temperature acquisition module, and the “multi-port parallel port driving method” was adopted to connect the controller; The controller used STM32F103 miniature controller as the main control chip; The digital storage module adopted Kingston Micro SD card to store temperature information; Display screen used Diven DGUS LCD screen. System principle block diagram and test platform were as shown in figure 1, 2, respectively.

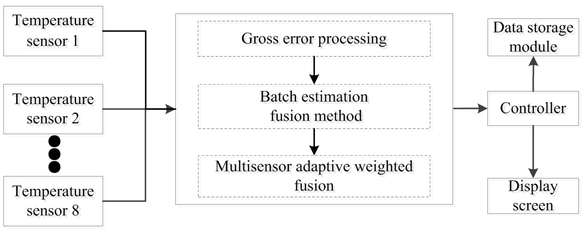

Figure 1: Temperature monitoring system structure diagram

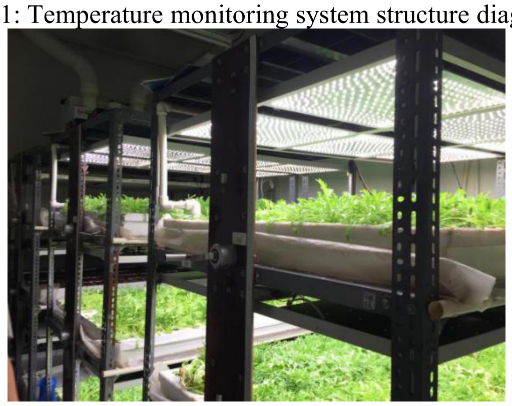

Figure 2: Temperature monitoring system test platform

3.2 Test analysis

Table 2 was three continuously measured temperature sampling values of 8 temperature sensors distributed in typical positions in the plant factory within a sampling period. Taking the measured data as an example (the real temperature reference value was 23 ℃), the fusion was carried out in accordance with the above methods.

Sensor		1	2	3	4	5	6	7	8
Tempera-ture measure-ment /℃	Group 1	20.8	21.9	22.6	23.3	23.7	24.7	23.0	22.9
	Group 2	21.4	22.4	23.8	22.2	25.1	24.4	22.3	21.6
	Group 3	22.7	23.2	24.4	24.0	28.8	22.9	21.1	23.2

Table 2: Temperature data in plant factory

First, Dixon criterion was used to process the gross error of three groups of data respectively. In accordance with the order from smallest to largest, 8 temperature values in each group were sorted. When $n = 8$, the effect of using r_{11} was the best, and $f_0(8, 0.1) = 0.683$ was obtained through looking up Table 1. We can obtain through calculation: there was no gross error in the first and second group, and there was gross error 28.8 in the third group, which shall be removed.

Three groups of removed temperature measurement data was consistency measurement data, and then the patch estimation fusion method based on average value was used to obtain the accurate measurement result. The batch processing was conducted on each group of data, each group of data was divided into two sub-groups, and the average value and standard deviation of each sub-group were calculated. The calculation results were as shown in table 3.

	Group 1		Group 2		Group 3	
	1	2	1	2	1	2
Average value	22.15	23.575	22.45	0.9983	23.575	0.7676
Standard deviation	1.0661	0.8302	23.35	1.6663	22.4	1.1358
Fusion value	23.0371		22.6877		23.2066	
Variance	0.429		0.7334		0.4044	

Table 3: Data after batch estimation

Finally, the data in table 3 was substituted into formula (12) to calculate the weights of three groups of data: W_1=0.4052, W_2=0.1386, W_3=0.456. According to the formula (9), the adaptive weighted fusion estimation value was: 23.0659, and the error was 0.0029. Meanwhile, the traditional algorithm average method was used to calculate the average temperature value and the error of three groups of data: 23.18℃ and 0.008. It can be seen that multi-sensor fusion data value was closer to the actual detected value, showing that the algorithm can obtain accurate measurement data, to minimize the measurement error.

Through the connection of temperature data within the continuous period, the data processing result was compared with that of the traditional arithmetic average method, and the result was as shown in figure 3. The figure showed the fused data values were smooth, with high reliability, achieving the desired effect.

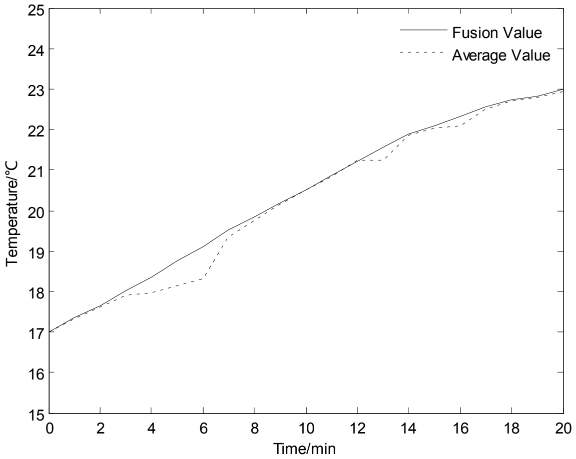

Figure 3: Temperature fusion curve

It can be seen from the above results, the result obtained by using the of multi-sensor data fusion algorithm was closer to the true value than that obtained by the arithmetic average method, and the error was smaller, effectively improving the accuracy of the temperature acquisition.

4 Conclusion

This paper used multi-sensor data fusion algorithm to measure the plant factory temperature. First, Dixon criterion was used to eliminate the gross error in the measurement data, then the accurate measurement result was obtained through patch estimation fusion method based on the average value, and finally the adaptive weighted fusion algorithm was adopted to conduct the fusion processing on the data, solving the problem of low accuracy of the traditional temperature measurement method. When the external factors had a greater interference to the sensor, the system can obtain accurate temperature data, small error, effectively guaranteeing the accuracy of plant factory control system criterion.

Acknowledgements

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