Design of Temperature and Humidity Monitoring System for Locust Greenhouse Based on Kalman Filter Fusion Algorithm

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Abstract: In this study, a new method based on Kalman filter fusion algorithm is proposed for the key problem of temperature and humidity monitoring in locust breeding greenhouses. The traditional method has many limitations in processing temperature and humidity data, and is susceptible to sensor failure, environmental interference and other factors, resulting in monitoring results deviating from the actual situation. Especially in the locust farming environment, locust activities may have a large impact on the monitoring system. To solve the above problems, Kalman filter fusion algorithm is used in this study. Kalman filtering is a recursive state estimation algorithm, which continuously updates the state estimates by predicting the current state and correcting the observed values, so as to realize the accurate estimation of the system state. In this study, we utilize the Kalman filter algorithm to fuse the temperature and humidity data collected by multiple sensors, and at the same time, we consider the system dynamic model to dynamically adjust the degree of data fusion, which improves the accuracy and stability of the monitoring data. Finally, this study compares the Kalman filter fusion algorithm with the simple averaging method commonly used in ordinary agricultural greenhouses, and the results show that the Kalman filter fusion algorithm can obtain more accurate and smooth data.

Keywords: Kalman Filter Fusion Algorithm; Locust Farming Greenhouses; Temperature and Humidity Monitoring; Accuracy; Stability

1.Introduction

Locust culture is closely related to environmental conditions, in which temperature and humidity, as one of the main influencing factors, play an important role in the growth and reproduction of locusts [1]. How to effectively monitor the temperature and humidity in the greenhouse is the key to improve the locust breeding yield. However, traditional greenhouse temperature and humidity detection systems often use the simple average method or extreme value rejection method to process the collected data. These methods are susceptible to the influence of sensor failure, environmental interference and other factors, and may cause the system to ignore the important information contained in the real data, so that the monitoring results deviate from the actual situation, affecting the system's accurate monitoring of the temperature and humidity environment and real-time response.

And unlike ordinary breeding greenhouses, in a special environment like locust breeding greenhouses, locust activities may have a greater impact on the temperature and humidity monitoring system [2]. Locust movement may cause the sensor position to be offset or damaged, resulting in the accuracy of the monitoring data being affected. In addition, locust activity may cause changes in air flow inside the greenhouse, which in turn affects the measurement results of the temperature and humidity sensors.

To solve the above problems, this study proposes a new method based on Kalman filter fusion algorithm to cope with the difficulties of data processing in the temperature and humidity monitoring system of greenhouses. Compared with the traditional method, the Kalman filter fusion method achieves dynamic adjustment and optimization of temperature and humidity data by utilizing data from multiple sensors and combining with the system dynamic model. Specifically, the method can effectively identify and filter outliers, and dynamically adjust the degree of data fusion according to the weights between sensors, thus improving the accuracy and stability of the data.

2.Design of Information Collection System for Locust Farming Greenhouses

The system design contains two parts, the upper and lower computer, the serial communication module is used to realize the information transmission between the upper and lower computer, and at the same time, the wireless Bluetooth communication module is used to realize the information transmission between each lower computer, and the system design generally shows a tree structure. The system model is shown in Figure 1. Among them, the upper computer function is designed by National Instruments (NILabVIEW programming language). It can receive and display the environmental data uploaded by the lower computer in real time. At the same time, it can also send control commands to the lower computer. The lower computer mainly contains the STM32F103C8T6 microprocessor, the environmental sensors, the controlled devices, and the modules such as the LCD display. This setup aims to realize the perception and monitoring of the environmental state of the greenhouse. Moreover, the wireless Bluetooth communication module can cover the whole environment of the greenhouse, and its low-power consumption can also prolong the service life. In addition, the serial communication module can transmit a large amount of data and a faster transmission rate to ensure the transmission efficiency of the upper and lower computer. The system design flowchart is shown in Figure 1.

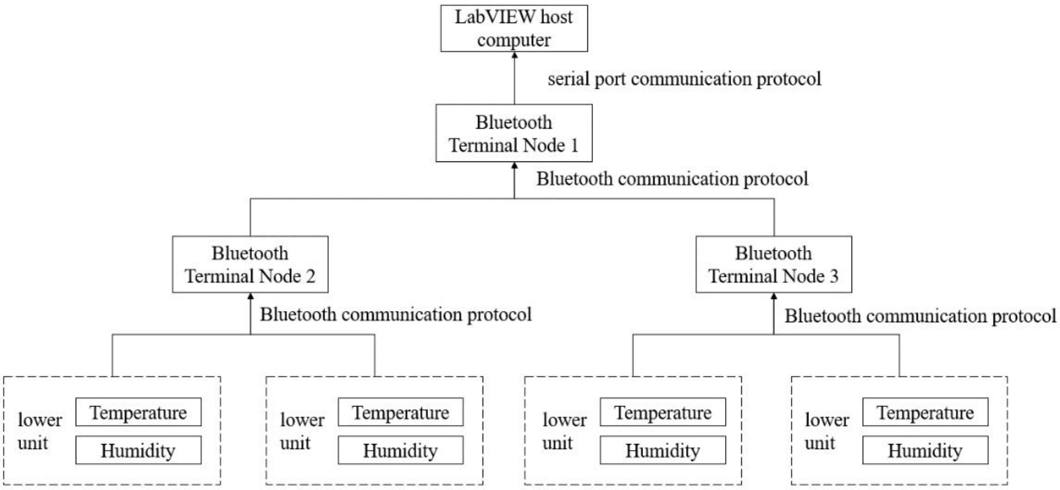

Figure 1. System Design Flowchart

3.Comparison of Fusion Algorithms

For the raw data collected by the temperature and humidity detection system of the above locust breeding greenhouses, this paper utilizes fusion algorithms for processing. Nowadays, the main fusion algorithms used are Kalman filter fusion algorithm, Bayesian estimation fusion algorithm, weighted average fusion algorithm, neural network fusion algorithm and simple average method [3].

4.Kalman Filter Fusion Algorithm

Kalman filter fusion is a classical data fusion algorithm that utilizes the process of state estimation and covariance updating to fuse data from multiple sensors by dynamically adjusting the weights. The algorithm combines the system dynamic model and observation data, which can effectively suppress the influence of noise and outliers, thus improving the accuracy and stability of data fusion.

4.1 Bayesian Estimation of Fusion Algorithms

The Bayesian estimation fusion algorithm is based on Bayesian theory, which utilizes the likelihood function of the a priori probability and the observed data to calculate the a posteriori probabilities of the data from different sensors and obtains the final estimation result by fusing these a posteriori probabilities. The algorithm can effectively fuse the information from multiple sensors by considering the uncertainty of the a priori information and the observed data, thus improving the accuracy and robustness of data fusion.

4.2 Weighted Average Fusion Algorithm

The weighted average fusion algorithm obtains the final estimation result by assigning different weights to different sensor data and weighting and averaging them. The algorithm is simple, intuitive and easy to implement, but it lacks flexibility in the processing of sensor data and cannot dynamically adapt to the changes in the system and the effects of noise.

4.3 Neural Network Fusion Algorithm

Neural network fusion algorithms utilize neural network models to learn and fit sensor data for data fusion and prediction. The complex relationships between sensor data can be better captured through the nonlinear fitting ability of neural networks, but it also requires more data and computational resources to train and optimize the network model.

4.4 Simple Mean Method

The simple average method is one of the most basic data fusion methods, where the data collected from multiple sensors are directly averaged in a simple way to obtain the final estimation result. The algorithm is simple and easy to use, but it is less robust to outliers and noise, and it cannot dynamically adjust the weights to adapt to changes in the system.

4.5 Comparison of Algorithms

When fusing data, it is necessary to consider the fusion to produce a good fusion effect, and to optimize the system from a global perspective. Table 1 shows the comparison of advantages and disadvantages of each level of data fusion processing.

Table 1. Comparison table of Advantages and Disadvantages of each level of Data Fusion Processing

Specificities	Kalman filter fusion	Bayesian estimation of fusion	Weighted average fusion	Neural network fusion	Simple average
Amount of information processed	Greatest	Moderate	Moderate	Greatest	Greatest
anti-interference capability	Best	Moderate	Moderate	Moderate	The least
Algorithmic difficulty	Hardest	Hardest	Moderate	Hardest	Easiest
Topicality	Best	Moderate	The least	The least	Moderate
Fault tolerance	Best	Moderate	The least	Moderate	The least

5.Kalman Filter Fusion Algorithm

In this paper, a very representative Kalman filter algorithm is chosen to fuse the obtained data. Kalman filtering through a layer-by-layer recursive way to carry out linear filtering, only need to use the estimated value of the previous sampling cycle plus the current measurement value can be an accurate estimation of the current state, the state equation completely reflects the rule of change of the estimated quantity [4]. This method will not take up too much storage space, the calculation steps are very clear and visible, real-time good anti-interference ability [5]. This paper takes the temperature signal as an example:

$$X(k) = AX(k-1) + BU(k) + W(k) \quad (1)$$

$$Z(k) = HX(k) + V(k) \quad (2)$$

where $X(k)$ is the predicted value; H is the relationship matrix; $Z(k)$ is the observed value; $U(k)$ is the control quantity of the system; A and B are the state parameters; $W(k)$ and $V(k)$ are the system noise and the observation noise, respectively; and their corresponding variances are Q and R, respectively.

The specific steps are as follows:

(1) Generate a priori estimate $X(k|k-1)$ based on the optimal result of the previous moment:

$$X(k|k-1) = X(k-1|k-1) \quad (3)$$

Where: $X(k|k-1)$ is the result of predicting moment k based on moment $k-1$; $X(k-1|k-1)$ is the optimal result at moment $k-1$.

(2) Update the a priori estimated covariance $P(k|k-1)$.

$$P(k|k-1) = P(k-1|k-1) + Q \quad (4)$$

Where: $P(k-1|k-1)$ is the k-moment covariance based on the $k-1$ moment.

(3) Calculate the Kalman gain $K_g(k)$ at the current moment:

$$K_g(k) = \frac{P(k|k-1)}{P(k|k-1)+R} = \frac{P(k-1|k-1)+Q}{P(k-1|k-1)+Q+R} \quad (5)$$

(4) The optimal estimate $X(k|k)$ at the current moment is calculated by combining the corrected estimate of the observations at the current moment:

$$X(k|k) = X(k|k-1) + K_g(k)[Z(k) - X(k|k-1)] \quad (6)$$

(5) An update operation is performed for the next momentary a priori estimate, i.e., updating the current momentary covariance $P(k|k)$:

$$P(k|k) = [1 - K_g(k)]P(k|k-1) \quad (7)$$

(6) Set the appropriate initial values X_0, P_0, noise values Q and R according to the actual reasonable settings, the above equation for the cycle iteration.

The Kalman filter workflow diagram is shown in Figure 2.

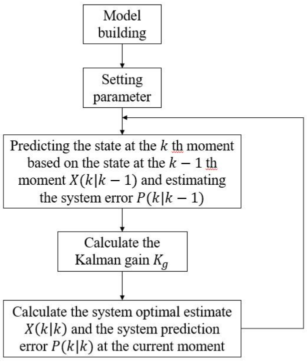

Figure 2. Kalman Filter Workflow Diagram

6.Simulation Results Analysis of Kalman Filter Fusion Algorithm

Before Kalman filtering the system, all parameters must be initialized by taking H=1 and A=1.And X_0=0, P_0=1, the value of R is taken as the mean value of the variance of the observed error in each column. Q is the global process error and assuming that it does not change with the change of the system, the root-mean-square of the error at the moment $k-1$ and at the moment k is denoted as the intermediate process error, then the intermediate process error is computed in each column, and their mean value is calculated, and this mean value is taken as the value of the global process error Q. The global process error Q is taken as the mean value of the observed error [6].

For the sensor acquisition data, the algorithm using Matlab simulation verification experiments, greenhouse greenhouse will be in a number of spatial areas to collect temperature data, in this case will be 5 temperature sensors to monitor the location of the 10 times the data collection, and will be collected and optimized values compared to the verification of the value [7]. The collected data and optimized values are shown in Table 2.

Observing Figure 3 and Figure 4, it is easy to get that when the system is running smoothly, the curve obtained by the simple average method fluctuates more and is more unstable. The curve obtained by the Kalman filter fusion method is more stable and smooth, and also improves the accuracy of the results.

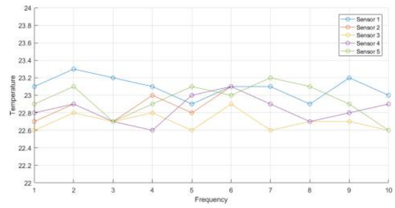

Figure 3. Line Graph of Sensor Measurements

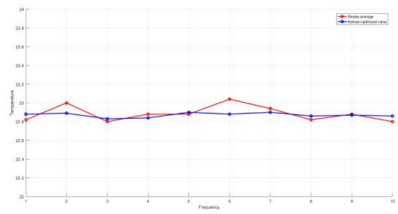

Figure 4. Comparison plot of Simple Mean and Kalman Optimized Values.

Table 2. Sensor and Kalman Optimization Data Sheet

Frequency	1	2	3	4	5	6	7	8	9	10
Sensor 1	23.1	23.3	23.2	23.1	22.9	23.1	23.1	22.9	23.2	23.0
Sensor 2	22.7	22.9	22.7	23.0	22.8	23.1	22.9	22.7	22.8	22.9
Sensor 3	22.6	22.8	22.7	22.8	22.6	22.9	22.6	22.7	22.7	22.6
Sensor 4	22.8	22.9	22.7	22.6	23.0	23.1	22.9	22.7	22.8	22.9
Sensor 5	22.9	23.1	22.7	22.9	23.1	23.0	23.2	23.1	22.9	22.6
Kalman optimized	22.68	22.69	22.83	23.04	22.90	23.02	22.95	22.83	22.87	22.80

8. Summary and Outlook

The research in this paper is a solution to the problem of damage or distortion of sensors in the shed due to the locusts' activities in the locust farming monitoring system [8]. Due to the special characteristics of locust's movement [9] , may cause the sensor position offset or damage as well as the changes of air flow inside the shed to affect the sensor's measurement results resulting in inaccurate monitoring system data [10] , this paper will be a node in the shed of multiple sensors collected data for Kalman fusion algorithm processing, and compared with the results of the simple average algorithm used in the ordinary agricultural shed, to get the conclusion that the Kalman The fusion algorithm can make the monitored data more stable and accurate conclusion. It opens up a new way of thinking for the modernized agricultural greenhouse monitoring system.

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References

[1] Ma J, Zhang ZH, and Li JT. Technology of large-scale artificial breeding of locusts. China Livestock and Poultry Breeding 16.03(2020):49.

[2] ZHANG Yuping, and ZHANG Zhiyong. Breeding technology of East Asian flying locust. Farmer's friend to get rich .24(2017): 149.

[3] Li Pengfei. Research and Application of Sensor Technology in Intelligent Vegetable Greenhouse Control System. 2021. Hunan Agricultural University, MA thesis.

[4] Tao Hongjiu, Gao Jun, Wu Wei. Multi-target detection and tracking based on Kalman filtering. China Society of System Simulation, Guizhou University, Guizhou Economic and Trade Commission, Guizhou Science and Technology Department, Guizhou Information Industry Department. Proceedings of Advanced Forum on Globalized Manufacturing and Symposium on Simulation Technology in the 21st Century. World Book Press, 2004: 4.

[5] Yannan Chen. Research on multi-sensor data fusion based on biased Kalman.2022.China University of Petroleum (Beijing), MA thesis.

[6] Chunling Wu, Yongping Li, Meimei Xie, et al. Adaptive volumetric Kalman filtering algorithm for noise characterization estimation. Chinese Society of Automation. Proceedings of the 2018 China Automation Conference (CAC2018). Chang'an University, 2018: 6.

[7] Han Shenyou. Refined temperature grid point forecast based on Kalman filter method. Chinese Meteorological Society. The 33rd Annual Meeting of the Chinese Meteorological Society S8 Numerical Model Product Application and Evaluation. Guangxi Meteorological Station, 2016: 3.

[8] ZHANG Dapeng, SHANG Zhonghua, WANG Rui, et al. Research and practice on the construction of locust ecological recycling aquaculture system. Journal of Shandong Agricultural Engineering College, 2023, 40(10): 30-33.

[9] WANG Wen. Grasshopper breeding technology. Sichuan Agricultural Science and Technology, 2008, (09): 41.

[10] WANG Zhicheng, XU Wensha, YANG Xue, et al. Research on ecological factors affecting locust artificial culture. Animal Husbandry and Feed Science, 2015, 36(09): 42-44.

