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Real-Time Environmental Data Collection and Fusion Method for Intelligent Greenhouses Based on Agricultural Internet of Things Technology

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In order to improve the real-time environmental performance of insulated, intelligent greenhouses and control various greenhouse parameters in order to meet production requirements, a real-time environmental data acquisition and fusion method is proposed for intelligent greenhouses, based on Agricultural Internet of Things Technology. By means of the Agricultural Internet of Things topology constructed using ZigBee technology, the ambient temperature, humidity and CO2 concentration data of intelligent greenhouse are collected in real time. The wavelet function is used to transform the collected environmental data, Mallat algorithm is used to calculate the low-frequency coefficients and high-frequency coefficients obtained from data transformation, the node distortion data is reconstructed, the wavelet analysis method is used to denoise the reconstructed data, and the data correlation is determined by the to the preprocessing results. The weighted algorithm, which has an improved support function, is used to fuse the real-time environmental data of intelligent greenhouses. The simulation results show that the proposed method has high accuracy and a short fusion time.

Keywords: Agricultural Internet of Things Technology; Intelligent Greenhouse; Real-Time Environmental Data; Wavelet Analysis.

1. INTRODUCTION

Food is essential for human health and survival. Agriculture is the primary industry that ensures the supply of food and contributes significantly to the national economy of China. With the rapid development of China's social economy, the agricultural production environment and agricultural land resources have been seriously damaged or put to other uses. Agricultural pollution is becoming increasingly serious, the quality and safety of agricultural products are often compromised, posing serious threats to people's health. Hence, agricultural production is being scrutinized and tested [1]. To address these issues, traditional agricultural practices should change to incorporate high-tech agricultural approaches based on scientific and technological developments. Because a large percentage of the population in China depends on agriculture for its livelihood, this industry has had to evolve and embrace high-tech agricultural practices in order to meet people's food needs, safeguard the jobs of agricultural workers, and advance the nation's economy. High-tech agriculture refers to high-quality and efficient greenhouse agriculture and industrialized agriculture, known as 'intelligent greenhouses' in developed

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countries. In China, intelligent greenhouses have been widely used in cold and arid areas such as those in the Northeast, North and Northwest. An intelligent greenhouse has several advantages: simple structure, high production efficiency, controllable internal environmental parameters, and convenient maintenance and use. It has become an important facility for high-quality and efficient production of crops. An intelligent greenhouse comprises several advanced technologies for agricultural production to create an ideal growing environment for crops that is not susceptible to factors in the external environment, and can maximize production efficiency and the quality of the produce. Smart greenhouses can modernize China's agriculture industry and ultimately benefit the people socially and economically [2]. Intelligent greenhouse technology has been developed and applied in automatic greenhouses, intelligent greenhouses, adaptive greenhouses and bionic greenhouses to improve the yield and quality of greenhouse crops, reduce the occurrence of diseases and pests, and minimize the impact of natural disasters. Greenhouse cultivation is based on the external environmental conditions favorable to crops, indoor crop types and crop growth conditions, and involves the regulation of various environmental parameters in the greenhouse to ensure that crops are growing in optimal conditions. to the use of smart greenhouses can reduce the crop growth cycle, improve the land utilization, prevent the occurrence of diseases and pests, and reduce the use of chemicals so as to improve crop quality and yield, and reduce labor intensity [3]. In addition to other functions, the real-time monitoring of the environment is the most important factor in the intelligent greenhouse. The growth and development of crops depends not only on their own biological characteristics, but also on their environment. The main external environmental factors affecting crop growth and development are the temperature, humidity, illumination and CO2 concentration. These data are real-time, multi-source and heterogeneous [4]. Due to the uneven distribution of environmental values in the intelligent greenhouse, in order to comprehensively evaluate this environment and ensure the accuracy of the automatic mechanism controlling the equipment, it is necessary to collect and combine the environmental data obtained by multiple sensors of the same type. Therefore, the real-time environmental data acquisition and fusion technology of intelligent greenhouses has become a priority of current research [5].

Zhu et al. [6] proposed a real-time environmental data fusion method for an intelligent greenhouse based on wavelet denoising and adaptive weighting. The collected data is processed through wavelet denoising to make it smooth and stable. The adaptive weighting algorithm is used to combine the multi-sensor data to obtain the optimal estimation value of the measured data. Xu et al. [7] proposed a sensor layout method based on data fusion. Using the temperature and humidity data of a tomato-growing environment in a greenhouse collected from 11 monitoring points, by means of missing value insertion by the BP neural network, together with batch estimation theory and the adaptive weighted average fusion algorithm, multi-sensor data was combined. By comparing the discrepancy between the fusion value and the original data, the best sensor data is selected, and the optimal sensor layout area is determined. The results show that the adaptive weighted average fusion method based on batch estimation can better reflect the characteristics of multi-sensor data than arithmetic average fusion and adaptive weighted average fusion. Ruan [8] proposed a data acquisition and fusion method known as Greenhouse Wireless Sensor Network Based on Hadoop, which uses ZigBee, wireless sensor, Internet of Things (IoT) and other technologies to collect greenhouse environmental parameters such as temperature, humidity, illumination and carbon dioxide concentration in real time, and uses the improved adaptive weighted fusion algorithm based on HBase historical data to combine the collected data. This makes it convenient for users to ascertain the overall greenhouse environment. The system database, consisting of MySQL+HBase hybrid storage mode, provides reliable storage and allows fast querying of a massive amount of greenhouse environmental data. Zhang et al. [9] proposed a multi-sensor data fusion method for greenhouse Internet of Things based on multivariate clustering statistical technology. The multi-sensor data related to greenhouse temperature, humidity and illumination are collected through the multi-sensor of Internet of Things, and denoised using the Kalman filter. According to the processing results, the multi-sensor data fusion of greenhouse IoT is carried out by using multivariate clustering statistical technology. The experimental results show that this method can produce better data fusion, reduce the data uncertainty and inaccuracy caused by various errors, and the errors regarding temperature, humidity and illumination are significantly less than those produced by the arithmetic mean value algorithm. Moreover, this approach can optimize the decision-making and regulation in regard to various environmental parameters. Although the economic benefits of greenhouse production need to be improved, the two methods proposed above are impractical as the multi-sensor data fusion of greenhouse IoT takes a long time, resulting in fusion inefficiency.

Agricultural Internet of Things (AIoT) Technology is a technology that uses network communication, radio frequency identification and sensors to collect and monitor the internal and external data of the crop-growing environment in order to achieve accurate, intelligent and scientific management of agricultural production. According to statistics, China's IoT industry contributes at least 100 billion yuan to the economy every year, and the Agricultural Internet of Things is an important part of the IoT industry. It has been widely used in areas such as field planting, agricultural machinery monitoring, garden facilities, aquaculture, livestock and poultry breeding, quality and safety tracing of agricultural products, and so on. As an important supporting technology of Agricultural Internet of Things, wireless sensor network (WSN) is the key to ensure the effective operation of the sensing layer and the transmission layer of the Agricultural Internet of Things. However, the Agricultural Internet of Things collects vast amounts of data, and has complex data transmission paths and a wide range of environmental interference information. Also, the energy and processing capacity of sensor nodes in WSN are very limited, presenting significant challenges to the efficient, stable and lasting operation of WSN, which is also

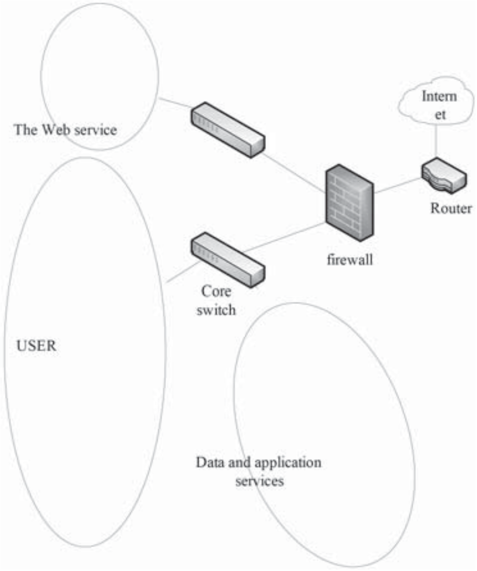


Figure 1 Topology of AIoT.

an important factor restricting the development of Agricultural Internet of Things. How to combine the data in WSN to reduce the amount of data transmission and improve the quality of data information so as to reduce the energy consumption of nodes, prolong the service life of WSN and improve the accuracy of monitoring results, has become an important area of research on the Agricultural Internet of Things. Therefore, to address the shortcomings of the aforementioned methods, this paper proposes a real-time environmental data acquisition and fusion method for intelligent greenhouses based on AIoT Technology, and evaluates the effectiveness of this method through simulation experiments, so as to provide data support for subsequent real-time environmental data analysis of intelligent greenhouses.

2. REAL-TIME DATA ACQUISITION AND FUSION METHOD FOR INTELLIGENT GREENHOUSE ENVIRONMENTS

2.1 Topology Design of AIoT

The topology of the AIoT network is a networking structure comprising ZigBee nodes which directly affect the performance of the network. Therefore, a specific ZigBee network topology must be selected according to different applications and functional characteristics. The current agricultural IoT network topology can be a plane network, hierarchical network, hybrid network or mesh network according to the function of nodes. This paper adopts the ZigBee hierarchical network as the field network structure for the acquisition of real-time environmental data in intelligent greenhouses [10].

The hierarchical network structure of the AIoT extends the traditional plane network structure, and divides the peer-to-peer network nodes into cluster head nodes for data aggregation and network organization, and member nodes that can only collect and forward data. In hierarchical networks, only cluster head nodes have perfect layer and network layer protocols, enabling only cluster head nodes to communicate with each other, while member nodes can only collect data and communicate with cluster head nodes. A hierarchical network improves the routing structure and management efficiency of the network through mandatory assignment of cluster heads, but increases the hardware cost. Another defect that cannot be ignored is the poor communication ability of member nodes, which reduces the robustness of the network [11]. Hence, the data transmission from the perceptual data acquisition site to the remote data center is completed in the transmission mode of ZigBee and GPRS relay. The design of this topology is shown in Figure 1.

2.2 Real-Time Environmental Data Acquisition of Intelligent Greenhouse Based on AIoT

In this paper, the real-time ambient temperature, humidity and CO2 concentration data for an intelligent greenhouse are collected through the topology of AIoT constructed above. The sensitivity and stability of the monitoring sensor directly determines the quality of the collected environmental data. Reliable and accurate environmental data is essential for subsequent data fusion [12]. Temperature sensors are used to detect the level of coldness and heat in an intelligent greenhouse. To monitor the temperature in a smart greenhouse, a negative temperature coefficient thermistor sensor is generally used. Its thermoelectric characteristics are:

$$R_t = R_0\, e^{E\left(\frac{1}{T}-\frac{1}{T_0}\right)} \tag{1}$$

where T represent the measured temperature, $T = 273 + t$ and T_0 represent the reference temperature, $T_0 = 273 + t_0$, R_t and R_0 represent the resistance value of the thermistor at the temperature of T and T_0, and E is the material constant of the thermistor [13].

According to the definition of temperature coefficient of the thermistor, a relative change α of resistance value can be expressed as:

$$\alpha = R_t \frac{E}{dt} \tag{2}$$

If there is no external power supply, the thermistor converts the temperature into a potential change sensor through the thermocouple temperature sensor. If the temperatures of the two metals are different, i.e., $T > T_0$, the thermoelectric potential $B(T, T_0)$ will be generated in the closed loop. By detecting the potential, the change in temperature can be sensed, and then converted to temperature which is measurable [14].

Humidity sensors are used to detect the level of moisture in an intelligent greenhouse environment, expressed as:

$$S = \frac{R_0}{\left(\frac{1}{T} - \frac{1}{T_0}\right)} \tag{3}$$

Another important aspect of environmental perception is the perception of CO^2 concentration. This paper uses carbon dioxide sensor to collect the real-time concentration of CO^2 in intelligent greenhouse. At present, electrochemical gas sensors are widely used for this purpose because they are very accurate, fast, simple to use, inexpensive, and have universal application. The basic principle underlying the detection of CO^2 concentration is the selective absorption characteristics of CO^2 molecules to light. That is, CO^2 molecules can absorb only those photons whose energy is exactly equal to the difference between its two energies [15]. When a beam of infrared monochromatic light or composite light passes through the gas to be measured, if the molecule of CO^2 to be measured selectively absorbs the light of some frequency bands in the radiation light, the absorption spectrum is generated. According to the mutual specificity of CO^2 molecular structures, the CO^2 absorption spectra of different molecular structures are different from each other. By detecting the absorption of light at a specific wavelength, the corresponding CO^2 concentration information can be obtained qualitatively and quantitatively [16].

2.3 Node Distortion Data Reconstruction

Because the acquisition of data through the AIoT will have a boundary effect and cause data distortion in disguise, the wavelet function is used to transform the collected topology to the real-time environmental data of the intelligent greenhouse, and the low-frequency coefficients and high-frequency coefficients obtained from the data transformation are calculated using the Mallat algorithm, so as to reconstruct the node-distortion data.

The wavelet function is used to transform the real-time λ-level data of the intelligent greenhouse environment, transmitted by the topology node α of the AIoT. The expression of the number of nodes X of the real-time environment distortion of the intelligent greenhouse due to the boundary effect is:

$$X = \lceil|(2^{\lambda} - 1)\beta\rceil| + (2^{\lambda - 1}) \tag{4}$$

where $\lceil| \ \rceil|$ stands for rounding up operation; β indicates the faulty node. Without the above calculation process, the faulty nodes will cause successive IoT failures, resulting in the distortion of the real-time environmental data of all nodes, resulting in the paralysis of the AIoT [17].

Taking the real-time environmental data of the intelligent greenhouse stored in a node as j vector set with j elements, the wavelet function is used to compare the j data in the vector to transform the real-time environmental data of the λ-level intelligent greenhouse. The low-frequency coefficients and high-frequency coefficients obtained from the real-time environmental data transformation are calculated using the Mallat algorithm. The decomposition process is as follows:

$$\begin{cases} x_o^{p+1} = \sum_{j-2o}^{m} X \\ y_o^{j+1} = \sum_{j=2o}^{j} gX \end{cases} \tag{5}$$

where x_o^{p+1} represents the o-th low-frequency coefficient obtained from the real-time environmental data transformation of level $p + 1$ intelligent greenhouse; y_o^{j+1} represents o high-frequency coefficients obtained from real-time environmental data transformation of level $j + 1$ intelligent greenhouse; m, g stands for low frequency and high frequency respectively. Assuming that there is no boundary expansion in the formula, the number of o-th level low-frequency distortion is $(2^{\lambda} - 1)(\beta_1 - 1)$ and the high-frequency coefficient is $(2^{\lambda} - 1)(\beta_2 - 1)$ [18].

Using the algorithm above, the reconstruction process is as follows:

$$y(n) = \sum_{j} \left(x_o^{p+1} + y_o^{j+1}\right)^2 \tag{6}$$

where $y(n)$ represents the reconstruction of real-time environmental data. Then the distorted real-time environment data quantity B can be obtained, expressed as:

$$B = y(n)(2^{\lambda} - 1)(\beta - 1) \tag{7}$$

Because of the node distortion obtained by the above algorithm, the amount of real-time environmental data is reconstructed, which is convenient for subsequent calculation. Assuming that the synthetic filter of wavelet function is the same as the respective analysis filter to some extent, if $B \geq X$, all the real-time environmental data of an intelligent greenhouse will be distorted [19].

2.4 Data Noise Reduction Processing

Because wavelet analysis is suitable for the noise reduction of data consisting of short-term high-frequency components and long-term low-frequency components without too much prior knowledge, it can be used to process the real-time environmental data of intelligent greenhouse. In addition, because the collection of greenhouse environmental parameters will be limited by the layout and use cost of sensors, the relatively few collection nodes, and the limited monitoring of data samples, the wavelet analysis method is used to reduce the noise of real-time environmental data so as to avoid the reduction and inconsistency of sample data caused by data elimination [20]. The wavelet denoising process is described below.

(1) Wavelet decomposition: select appropriate wavelet basis function, determine the number of decomposition layers, and decompose the original data using Mallat algorithm; If the original data is $f(x)$, the low-frequency part under scale *j* is *A* and the high-frequency part is $D_i f$ with level 0 as the highest resolution direction, the original data can be finally decomposed into:

$$f(x) = AJ + \sum_{j=1} D_i f \tag{8}$$

where J is the number of dispersion layers.

(2) Threshold quantization of high-frequency coefficients: select an appropriate threshold to quantify the high-frequency coefficients from layer 1 to layer N;

(3) Wavelet reconstruction: according to the low-frequency coefficients of the *N*th layer decomposed by wavelet and the high-frequency coefficients of the 1st to *N*th layers after quantitative processing, wavelet reconstruction is carried out to obtain the real-time environmental data of the intelligent greenhouse after noise reduction.

2.5 Data Correlation Calculation

In order to combine the same data into the same class, the specific steps of data association calculation are as follows:

First, combined with probabilistic data association algorithm, filter and estimate the real-time environmental data of intelligent greenhouse in each sensor;

Second, after estimation, classify the real-time environmental data of intelligent greenhouse and express it as follows:

$$q_i = \frac{|e_a|}{\sum_{n}^{i=1} |e_a|} \tag{9}$$

In the formula, e_k represents the measured value at time a.

Third, calculate the weight coefficient and express the formula as follows:

$$R_e = \frac{\sum_{i=1} b \cdot B_j}{1 - a} \tag{10}$$

where $\sum_{j=1} b \cdot B_j$ represents the conflict function of real-time environmental data of two intelligent greenhouses. The greater the conflict, the less is the correlation between the two data; the smaller the conflict, the smaller will be the difference.

Fourth, state update. The comprehensive state update equation is expressed as:

$$X_f = \sum_{n}^{i=1} \mu_i \cdot R_e \tag{11}$$

where μ_i represents the status update parameter of the *i*-th index.

The correlation calculation above provides the basis for data fusion.

2.6 Data Fusion of Real-Time Environment in Intelligent Greenhouse

After the correlation data have been obtained, the weighted algorithm, the weighted algorithm based on improved support function is used for the fusion of real-time environmental data of an intelligent greenhouse. The improved support function can reduce discrepancies between data fusion results for similar sensors, improve the fusion accuracy, and optimize the data fusion effect of real-time environment in intelligent greenhouses.

First, build an improved support function:

$$\sup(m, n) = SN(m, n, K, \beta) \tag{12}$$

where sup(*m*, *n*) represents the support function, *K* represents the support amplitude, which is generally set to 1 for ease of calculation, β represents the support attenuation speed. The higher the β, the faster is the support attenuation. The closer two measurements in a set of isomorphic perception data are, the greater will be the value of the mutual support function.

Let the values of temperature sensor i and temperature sensor j at time t after data preprocessing be $X_i(t), X_j(t)$ respectively, and substitute it with the improved support function:

$$\sup(X_i(t), X_j(t)) = SN(X_i(t), X_j(t), K, \beta) \tag{13}$$

Set the matrix of mutual support between sensors as a_{ij}, then the sum of support of all other sensors to sensors is:

$$sum\,SN(X_i(t)) = \sum_{j=1}^{N} a_{ij} \tag{14}$$

According to the power mean square operator, the optimal fusion weight of sensor i is w_i, then the optimal estimation value $X(t)$ of temperature sensor group after power mean square weighted fusion is:

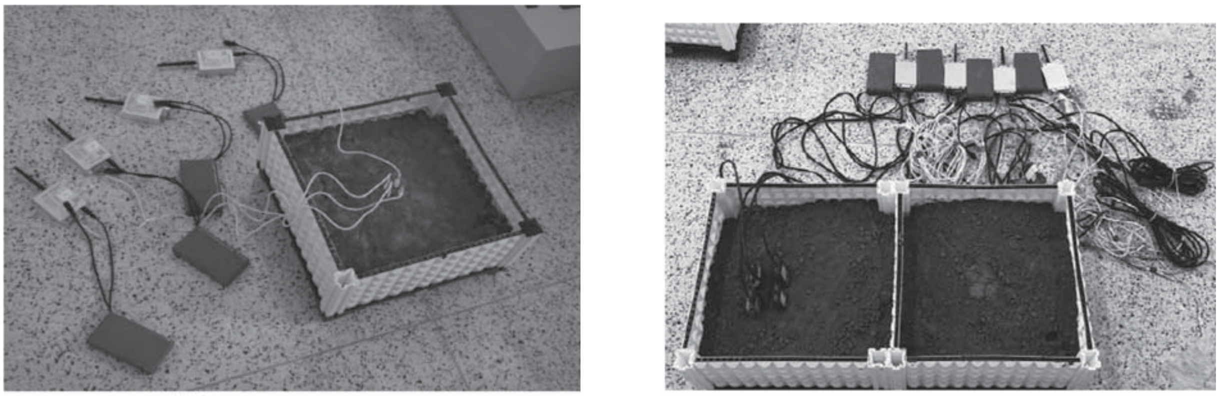
$$X(t) = \frac{\sum_{i=1}^{N} (w_i * X_i(t))}{\sum_{i=1}^{N} w_i} \tag{15}$$

In the formula, $X(t)$ represents the optimal value after homogeneous data fusion, $X_i(t)$ represents the measured value of each sensor of the same type after data consistency detection, and *wi* represents the optimal fusion weight of each sensor.

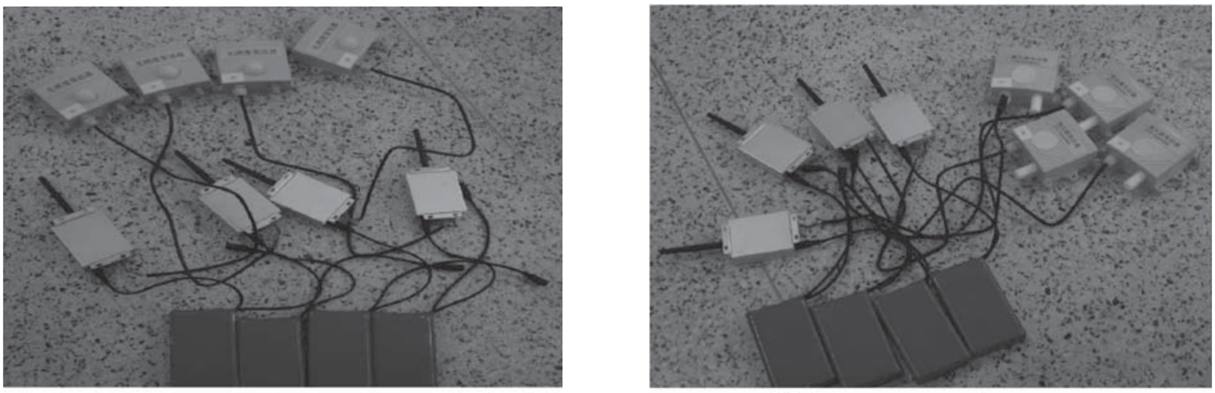
3. SIMULATION EXPERIMENT ANALYSIS

3.1 Introduction to Experimental Environment

The experimental greenhouse used in this study is one of a group of greenhouses is a greenhouse group in the ocean current map science and Technology Park of an agricultural university. The greenhouse complex includes 13 solar greenhouses and 3 multi-span greenhouses, all of which



(a) Temperature sensor (b) Temperature and humidity sensor



(c) Light intensity sensor (d) CO_2 concentration sensor

Figure 2 Experimental test environment.

are east-west. The experimental greenhouse chosen for the experiments was No. 4 greenhouse, 70 m long and 5° south by west. The ridge height is 4 m, the span is 8 m. The daylighting angle is $20^\circ 17'$; The wall adopts brick with clay, the rear insulation wall is 2.7 m high and 1.4 m thick, and the east and west gables are brick walls with a thickness of 0.5 m. The covering of the greenhouse is transparent polyvinyl chloride film, and the thermal insulation is a covering consisting of an outer layer waterproof silk and inner layer of cotton fiber; The load-bearing is a double diagonal-drawn steel skeleton; Inside, there is a 0.6 m-wide cement path near the back wall.

Firstly, the group of soil temperature sensors and the group of soil temperature and humidity sensors were placed in the test soil sample. The probe components were positioned 0.07 m and 0.05 m respectively on the ground surface. The light intensity sensor and CO^2 concentration sensor were placed on the greenhouse floor, ensuring the test elements were upright, and reducing the distance between the sensors as much as possible. The experimental test environment is shown in Figure 2.

3.2 Experimental Scheme

In order to verify the effectiveness of the real-time environmental data acquisition and fusion method of intelligent greenhouse based on AIoT Technology in practical application, a greenhouse was selected as the test object, and a longitudinal section inside the greenhouse was selected for sensor layout. The location of the measuring points is shown in Figure 3, and the layout and actual installation of the measuring points are shown in Figure 4.

During the test, 20 measuring points were position in the longitudinal section. Due to the different types and quantities of sensors, in order to facilitate data processing and analysis, the first underground layer (5 in total) was used for soil temperature and humidity sensors, the second to third underground layers (15 in total) were used for soil temperature sensors, and 8 light intensity and CO^2 concentration sensors are arranged on the second and third floors respectively, connected to different measuring points through wired connection.

After the sensor nodes had been positioned according to the test scheme depicted above, the sampling frequency of the central sink node of the wireless ad hoc network was set to 1min, and the 20 data acquisition nodes were divided into five groups according to the address order, with four acquisition nodes in each group. All acquisition nodes were powered by a lithium battery. After the sensor was deployed, 20 acquisition nodes were powered up; then the researchers waited 5 ∼ 10 s to enable the wired data acquisition network to complete the initialization process. Finally, the central sink node was powered up, the whole network was initialized, and a wireless data transmission link was established. During the test, the central sink node sent data-acquisition instructions every 1 min, and then completed the data aggregation task of 20 acquisition nodes according to the packet ad hoc network protocol. Each time it received the data returned by one node,

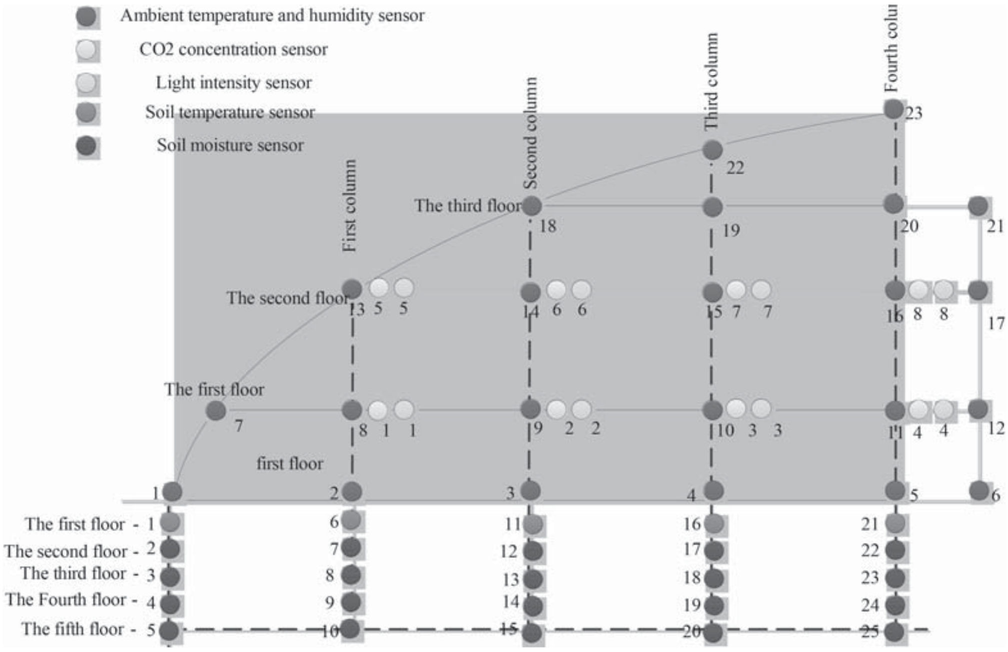


Figure 3 Location of measuring points.

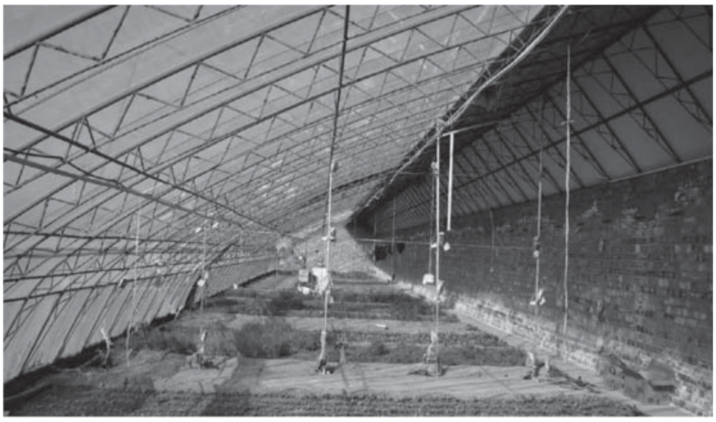


Figure 4 Layout of measuring points.

Table 1 Technical parameter setting of ambient temperature sensor.

Parameter name	Parameter value
Temperature measurement range	$-40 \sim +125°C$
Temperature measurement accuracy	±0.3°C
Temperature resolution	0.01°C
Temperature response time (63%)	Typical value 4 s
Temperature repeatability	±0.1°C
Supply voltage	DC 5 V$\sim$ 12 V
power waste	$\leq$ 0.1 W

it analyzed and processed the data, and sent it to the touch screen software system and PLC controller via the serial port. The whole system operated non-stop for 2D.

3.3 Parameter Setting

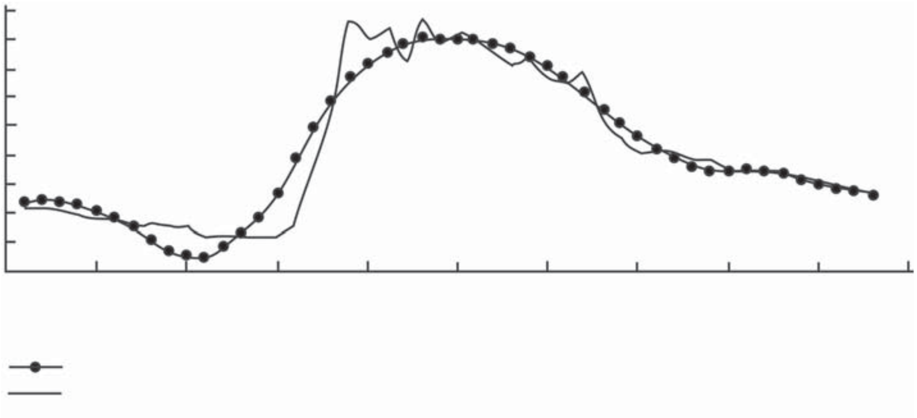
The technical parameters of the ambient temperature and humidity sensor are shown in Table 1 and Table 2.

3.4 Wavelet Denoising Preprocessing

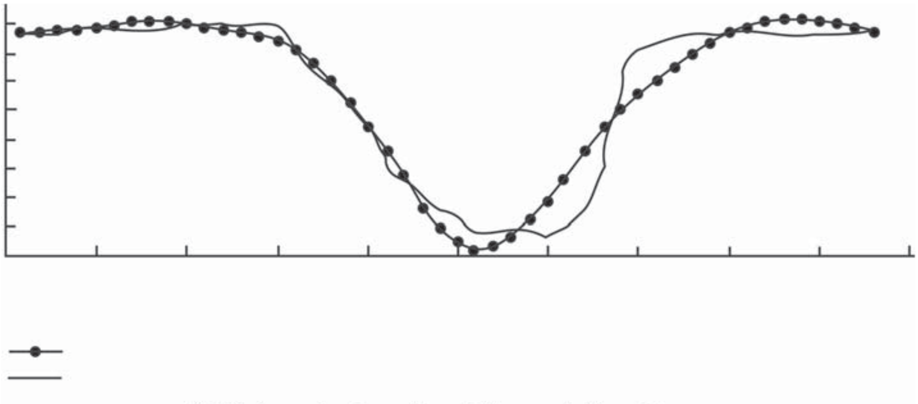
MATLAB software was used to denoise the temperature and humidity data. After a comparison was made of many test results, the db5 wavelet basis function was finally selected for three-layer decomposition, the threshold function of each layer was selected as the soft threshold function, and the wavelet analysis method was used for threshold estimation. The comparison results between the denoised reconstructed data and the original sample data are shown in Figure 5.

Table 2 Technical parameter setting of ambient humidity sensor.

Parameter name	Parameter value
Humidity measurement range	0 ~ 100% RH
Humidity measurement accuracy	±2% RH
Humidity resolution	0.03% RH
Temperature response time (63%)	Minimum 5 S
Humidity repeatability	±0.1% RH
Output interface	Standard RS485 bus/Modbus Protocol
Material Science	ABS



(a) Noise reduction of temperature acquisition data



(b) Noise reduction of humidity acquisition data

Figure 5 Noise reduction effect of temperature and humidity acquisition data.

It can be seen from Figure 5 that the temperature and humidity curves fluctuate greatly in the middle period. After wavelet denoising, the data curve has no singular value, is very smooth and stable, and has a good noise reduction effect.

3.5 Comparison Results of Real-Time Environmental Data Acquisition and Fusion Accuracy of Intelligent Greenhouse

The results obtained by the method proposed in this paper are compared with those of [6] and [7] to determine the accuracy of results obtained by each of these methods used for the acquisition and fusion of real-time environmental data obtained from a smart greenhouse. The comparison results are shown in the form of graphs and tables. First, see Figure 6.

As shown in Figure 6, the real-time acquisition and fusion of environmental data obtained from an intelligent greenhouse achieves an accuracy of 100% when our proposed AIoT Technology is applied, outperforming the methods proposed in [6] and [7].

3.6 Comparison Results of Real-Time Environmental Data Acquisition and Fusion Time in Intelligent Greenhouse

See Table 3 for table analysis.

As shown in Table 3, the time consumed by the intelligent greenhouse real-time environment data acquisition and fusion method based on AIoT Technology proposed in this paper is

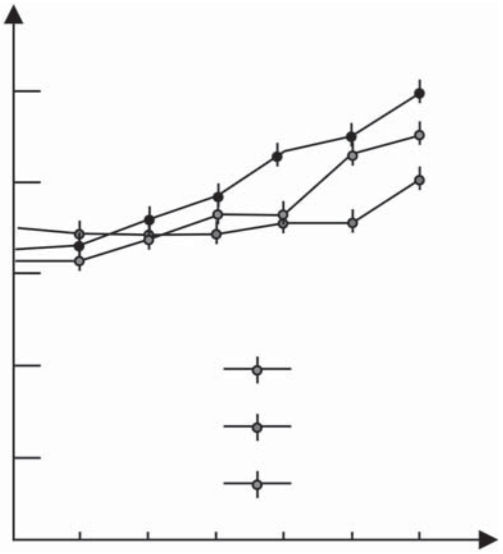


Figure 6 Comparison of results obtained by three methods used for environmental data acquisition and fusion.

Table 3 Comparison results of different methods.

Number of experiments/time	Proposed method	Reference [6] methods	Reference [7] methods
10	10.23	16.55	25.86
20	10.56	16.96	26.12
30	10.99	17.25	27.02
40	11.26	17.68	28.52
50	11.96	18.22	29.02
60	12.05	18.96	30.55
70	12.66	19.20	31.52
80	12.96	19.85	32.66
90	13.56	20.55	33.02
100	14.95	20.96	34.09

within 14.95 s, which is less than the time required by the methods proposed in [6] and [7].

4. CONCLUSION

The AIoT approach can collect accurate data, and achieve reliable transmission and intelligent processing of information. It is based on IoT technology that can be applied to various sectors including agriculture. In China, this technology can accelerate the transformation of agriculture from one that relies on traditional practices to one that uses modern technological means to improve agricultural production, produce high-quality crops, and protect the environment. AIoT information technology enables the real-time monitoring of animal and crop farming, including soil and environment (macro to micro), and improves the fine management level of agricultural production. To make the most efficient use of agricultural resources, reduce production costs, improve the ecological environment and produce better-quality agricultural products. IoT technology is widely used in many agricultural contexts. By means of sensor technology, we can obtain more accurate information about the crop, the agricultural environment and the operation of agricultural machinery, so as to provide richer real-time data for intelligent agriculture. By applying the AIoT technology, people can more conveniently and accurately obtain the parameters of a crop's cultivation environment, thereby implementing intelligent agricultural practices. At present, China's agricultural greenhouses are operated by both individual farmers and large-scale production companies. If we want to achieve the optimum automation of intelligent greenhouses, we must acknowledge that we cannot rely totally on human observations and control, which are susceptible to error and are a waste of human resources. Therefore, for modern greenhouse management, a complete greenhouse automatic control system is needed to control various parameters of the greenhouse to meet production requirements. Factors such as temperature and humidity, light intensity, CO^2 concentration, moisture and other environmental factors play an important role in the cultivation of crops. With traditional farming practices, these factors are monitored by means of human observation, which is susceptible to inaccuracy and may lead to decisions that have a negative impact on the yield and the quality of crops. The real-time environmental data acquisition and fusion method proposed in this paper involves three steps: real-time acquisition of environmental data of intelligent greenhouses, data processing, and data fusion. It provides a foundation for improving the performance of greenhouse thermal insulation, optimizing the greenhouse structure, efficiently arranging the crop planting lay-out, simplifying the greenhouse test scheme, and perfecting the regulation strategy.

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