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Multinode temperature monitoring method for digital agricultural planting based on a wireless sensor network

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Abstract: In order to monitor the temperature of agricultural planting in real time and avoid losses in the yield and quality of crops due to excessive temperature fluctuation, a multinode temperature monitoring method for digital agricultural planting based on a wireless sensor network (WSN) was proposed herein. First, the WSN structure for the digital agricultural temperature monitoring system was designed, and then the overall structure of the digital agricultural planting multinode temperature monitoring system was designed by combining it with the upper computer to collect agricultural planting temperature data. Next, the characteristics of the agricultural planting temperature data were extracted, and the data were transmitted to the upper computer by establishing a temperature transmission route. Then, the efficiency of the temperature anomaly monitoring was optimized based on multiple input multiple output (MIMO) mode. Finally, the real-time collected temperature value was input into a Bayesian classifier to monitor the temperature anomaly, determine the type of temperature anomaly, and send a warning to the administrator, who, based on the type of warning, takes the appropriate measures to adjust the multinode temperatures at the agricultural planting points. The experiments showed that this method had strong data transmission ability, and the survival time of the data transmission nodes was longer, and the energy consumption of the data transmission was less, and the accuracy of the abnormal temperature monitoring was above 96%. The results showed that this method can accurately monitor abnormal temperatures and provide a warning in real time, accurately control the temperatures of the agricultural planting points, and promote the digital development of agriculture.

Key words: Wireless sensor network, MIMO mode, upper computer, abnormal temperature, digital agriculture, Bayesian classifier

1. Introduction

Digital agriculture (Chandra and Collis, 2021) was formally proposed in 1997 by the American Academy of Sciences and the Chinese Academy of Engineering. It refers to intensive and information-based agricultural technology (Kpaka et al., 2021) under the support of geoscience space and information technology. It refers to remote sensing (Emmanuel and Michael, 2022), the geographic information system (Irtem and Sacin, 2012), global positioning system, computer technology, communication and network technology, automation technology and other high and new technologies and geography (Talaat et al., 2020), agriculture (Parrish and Fike, 2005), ecology, plant physiology, soil science, and other basic disciplines organically combined, to achieve the real-time monitoring of crops (Mohanty and Mallick, 2022) and soil from macro to micro in the process of agricultural production, in order to achieve crops. Through digital agriculture, data about the growth, development status, diseases and insect pests (Cividanes, 2021), water and fertilizer status, and corresponding environment are obtained regularly, and a dynamic spatial information system is generated to simulate the phenomena and processes in agricultural production, so as to achieve the purposes of rationally utilizing agricultural resources (Thorup-Kristensen et al., 2020), reducing production costs, improving the ecological environment, and improving crop products and quality. Digital agriculture is a modern agriculture model that takes information as the factor of agricultural production and uses modern information technology to visually express, digitally design and provide information management of agricultural objects, the environment, and the whole process. Digital agriculture allows information technology and all links of agriculture to be effectively integrated, which is of great significance to the transformation of traditional agriculture and the agricultural production mode.

At present, many scholars have studied the monitoring of digital agricultural planting areas via computer technology. For example, an experiment was conducted

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at the research farm of Tarbiat Modares University to investigate the effects of Wi-Fi electromagnetic waves on the germination, growth characteristics, and fatty acids of Camel Peganum seeds. They exposed the seeds to Wi-Fi electromagnetic radiation at distances of 15 cm (ER 15) and 25 cm (ER 25) from a modem for 24 h (Khashayarfard et al., 2023). Monitoring of the humidity, temperature, and gas of the agricultural planting based on the Internet of Things and Arduino Uno was investigated (Mohammed et al., 2022). The Arduino Uno and Wi-Fi modules were used to process and transmit the sensing data of the agricultural planting to ThingSpeak cloud, and the monitoring report of the agricultural planting environment obtained by the cloud computing was conveyed to the users. The carbon mineralization and temperature sensitivity of a corn-wheat system was also studied by Sandeep et al. (2016), and cultivated T-6 = 100% to determine the recommended dose of organic nitrogen at different temperatures to obtain the heat-sensitive parameters related to carbon mineralization and complete the monitoring of the environmental temperature. The design of a corn field temperature and humidity monitoring system based on a wireless sensor network (WSN) was developed by Li et al. (2020). Based on the ZigBee WSN, remote data transmission and real-time monitoring of the soil temperature and humidity environment data at various stages of corn growth was performed, so as to dynamically collect, analyze, and process the relevant data and obtain information about the soil temperature and humidity conditions and changing conditions in the study area in real time.

Although the above method can complete the temperature monitoring of digital agriculture, it also has some shortcomings, such as using wired data transmission, it cannot be used in large-scale digital planting, the efficiency of wireless transmission is slow, data transmission consumes a lot of energy, the survival time of the clustering algorithm is low, and the warning is not given fast enough after a high temperature is detected. Based on the above research results, a multinode temperature monitoring method for digital agricultural planting based on a WSN was proposed herein. The WSN adopted a clustering routing algorithm to determine the topological structure, which was free to form, fast at data transmission, and offered wide coverage.

2. Digital agricultural planting multinode temperature monitoring

2.1. Overall structure design of the digital agricultural planting multinode temperature monitoring system

By designing a multinode temperature monitoring structure of a WSN, the whole agricultural planting area can be covered, and the temperature of multiple nodes can be monitored in real time. The overall structure of the digital agricultural planting multinode temperature monitoring system included 2 parts, a WSN and an upper computer. A WSN is a 3-tier architecture composed of a sensor node (SN) (Javaid, 2022), gateway node (GN), and base stations (BS). The upper computer is responsible for receiving the multinode temperature data of the digital agricultural planting area collected and transmitted by the WSN and applying the information processing technology to detect abnormal temperatures.

Among them, the sensor network is a wireless network (Singh et al., 2022) composed of a group of wireless sensors, and its purpose is to cooperatively perceive, collect, and process environmental information in the planting area, such as the temperature, and then send this information to the temperature monitoring manager through the wireless network. The wireless sensor, sensing object (planting area temperature), and manager are the three fundamental elements used to achieve digital agricultural temperature monitoring. Wireless sensors communicate with both each other and temperature monitoring managers through wireless networks, transmitting various types of information about planting areas and representing them digitally. In order to establish a communication path, it is the basic function of the WSN to cooperatively perceive, collect, process, and send planting temperature information between the wireless sensors and temperature monitoring managers.

In WSNs, some or all of the nodes can move, and the topology of the sensor networks will change dynamically with the movement of the nodes in the planting areas. When transmitting planting temperature data, each node can play the role of a router, and has the ability to dynamically search, locate, and restore connections to transmit data. This network structure plays an important role in digital agricultural temperature monitoring. The structure of the WSN is shown in Figure 1.

The first layer: the sensing module. Several temperature sensors are arranged in the multinode temperature monitoring area of the digital agricultural planting. The whole multinode temperature monitoring area of the digital agricultural planting is divided into many clusters based on certain standards (such as communication range and geographical location). They usually operate independently, sensing media, collecting the raw planting area temperature data, and forwarding them to neighboring nodes, and then sending them to the second layer.

The second layer: the processing module. It is a resource-rich driving device. These devices allocate rich resources to the agricultural planting areas that need intelligent monitoring, they are the GNs, as the cluster heads of each cluster. Each GN maintains its own unique ID, and based on the number distribution of clusters, it can collect raw temperature data from the temperature SNs

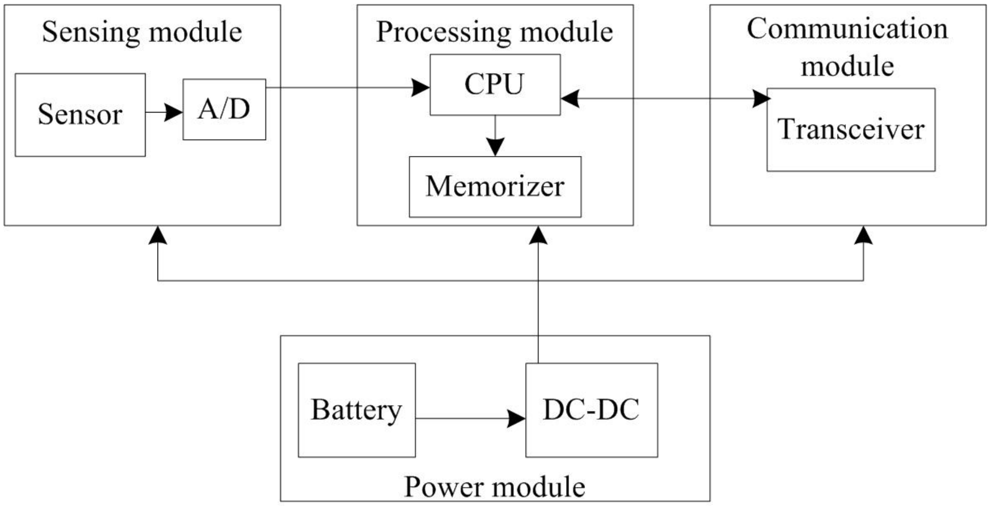

Figure 1. Wireless SN structure.

in the agricultural planting area in the cluster, and then use data aggregation technology to sort out the data and forward it to the third layer.

The third layer: the communication module. High-frequency sensing and communication nodes (such as RSCWins-Hidra nodes) constitute the third layer of the network and serve as the BS of WSNs, which perform the collection and transmission of the multinode temperature data in the agricultural planting areas. These nodes have strong data processing ability, memory, transmission ability, and long battery life, and the BS keeps in touch with users through wireless media (such as the Internet).

Through the results of the 3-layer system of WSN, the temperature collection and transmission of digital agricultural planting can be completed more conveniently, quickly, and intelligently, and the temperature monitoring data of multinodes in the digital agricultural planting area can be obtained, so as to complete the temperature monitoring of the planting area. The overall structure of the digital multinode temperature monitoring process for agricultural planting is shown in Figure 2.

In Figure. 2, the WSN is divided into several clusters, and each cluster has a GN for controlling the SNs in the cluster; The GNs of different clusters communicate with each SN in the cluster to exchange the agricultural planting temperature data collected by the SNs, and they then use the GNs to forward the collected agricultural planting temperature data to the nearby BSs and upload them to the upper computer.

2.2. Temperature data transmission

2.2.1. Extraction of the temperature characteristics in the planting area

In the process of agricultural planting temperature data collection, there will be problems such as sensor failure, data transmission errors, or environmental interference, which will lead to inaccurate data quality. Therefore, the characteristics of the collected multinode temperature data of agricultural planting are extracted by the upper computer. The extracted characteristic value of temperature wave form T include the mean value T_{avg}, variance T_v, effective value T_{rms}, peak index T_{cf}, and margin index T_e. With the temperature data set as $t_p = \{x_1, x_2, \cdots, x_{20}\}$ (temperature values collected by the sensors nearly 20 times), the calculation formulas of the 5 characteristic values are given in Eqs. (1) to (5) below:

Mean value:
$$T_{avg} = \frac{\sum_{n=1}^{20} x_n}{20} \tag{1}$$

Variance:
$$T_v = \frac{\sum_{n=1}^{20} (x_n - T_{avg})^2}{20} \tag{2}$$

Valid values:
$$T_{rms} = \sqrt{\frac{\sum_{n=1}^{20} x_n^2}{20}} \tag{3}$$

Peak index:
$$T_{cf} = \frac{max(t_p)}{T_{rms}} \tag{4}$$

Margin value:
$$T_e = \frac{T_{rms}}{T_{avg}} \tag{5}$$

By feature extraction of the temperature data, the original data can be compressed and optimized, the data volume can be reduced, and the efficiency and speed of the data transmission can be improved.

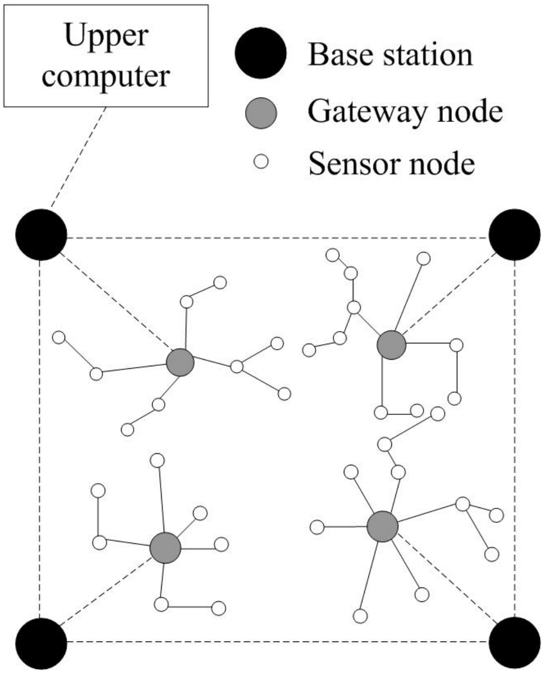

Figure 2. Architecture of the 3-layer WSN.

2.2.2. Establishing the temperature transmission route

The amount of data after temperature feature extraction is smaller than the original data, but it may still be a certain amount of data. Without proper route establishment, data transmission may face the problem of insufficient bandwidth or network congestion. In order to improve the efficiency of energy utilization, facilitate management when wireless sensors transmit planting temperature data, and enhance the efficiency of information transmission in the whole planting area, it is necessary to cluster the wireless sensors, to ensure that the data can be stably and efficiently transmitted to the target device.

The clustering routing algorithm in this research was divided into 3 stages: initializing the WSNs, establishing the network clusters, and establishing the network routing (Sun and Wan, 2022).

2.2.2.1 Initializing the WSNs

Uneven deployment of the nodes in the WSNs facilitates the transmission of the planting temperature data (Chen et al., 2022), and the network enters the initialization stage. Based on the digital agricultural planting area's size, network scale, and parameters of WSNs monitored by wireless SNs, the number of layers in WSNs is determined. Corresponding settings are then configured accordingly. In order to make the distance between the cluster heads of the adjacent layers approximately equal when the WSN transmits multinode temperature data in the planting area, and to prevent the multipath attenuation phenomenon in the communication between the cluster heads, the number of network layers, n, needs to meet:

$$n = T\left[\frac{2R}{d_0}\right], \forall i\left(i \in [1, n] \middle| r_i - r_{i-1} \leq \frac{2R}{d_0}\right) \quad (6)$$

The sink node in the wireless network broadcasts a network initialization message to the network, which includes the monitored radius of the digital agricultural planting area, R, the distance calculation factor, df, and the number of network layers, n, such information about the parameters. After receiving the network initialization message, the wireless SN calculates the distance from the sink node according to the signal power when receiving the message and the information sum of the network initialization message, which is expressed as given in Eq. (7):

$$d = \frac{nc}{4\pi f}\sqrt{\frac{p_t}{p_r}} \quad (7)$$

Here, $\frac{c\sqrt{p_t}}{4\pi f}$ represents a common factor, p_r indicates the signal power when the SN receives the message, and p_t represents the signal transmission power of the sink node. After obtaining the distance between the wireless SN and the sink node, d, the level of the SN is calculated and evenly layered. At this time, the WSN initialization is complete, and the cluster establishment stage begins.

2.2.2.2. Establishing the network clusters

The establishment stage of the temperature monitoring WSN cluster consists of 2 stages: cluster head election and the cluster structure.

2.2.2.2.1 Cluster head election

The cluster head of the routing algorithm for temperature data transmission in the planting area is elected by a random strategy. Each wireless SN calculates the ideal cluster head ratio of the layer according to its own layer when transmitting the temperature data of the planting area, which is expressed as:

$$p_i = \frac{dp}{i^2} \quad (8)$$

Then, it calculates the residual energy of the nodes and the ratio of ideal cluster heads to get the threshold of each node, which is expressed as:

$$P = \begin{cases} p_i, E_n \geq E_{threshold} \\ 0, E_n < E_{threshold} \end{cases} \quad (9)$$

Here, i represents the level at which the node is located, p_i expresses the ideal cluster head ration in layer i, $E_{threshold}$ indicates the energy threshold within the cluster, and E_n represents the residual energy of the node.

Each wireless SN generates a number between 0 and 1 and compares the threshold with this number. If it is less than the threshold, the node is elected as the cluster head; otherwise, it is a noncluster head node. In this research, the uneven clustering strategy was used in the process electing the cluster head. Therefore, with the increase in the network level, the proportion of ideal cluster heads decreased, and the further they were from the aggregation nodes, the more nodes there were, and the larger the cluster radius was. Therefore, the clustering could be adjusted according to the network coverage of the agricultural planting areas. After electing cluster head, it moved on to the stage of establishing the cluster structure.

2.2.2.2.2 Establishing the cluster structure

After the cluster head election of the wireless SNs is complete, the cluster head node should initialize its cluster member table, and the cluster head then broadcasts the cluster head message to the other nodes in the planting area with fixed transmission power, instructing the other nodes in the agricultural planting area to be elected as cluster heads themselves. After receiving the information, the other noncluster head nodes update the corresponding adjacent cluster head table, select a cluster head closest to themselves as their own cluster, and send a message to the cluster head to apply to join the cluster. After receiving the message to apply to join the cluster, the cluster head registers the information of the node in the cluster member table and sends a cluster confirmation message to the node. After receiving the confirmation message sent by the cluster head, the node changes its status to a cluster member. When the cluster head receives the information of all of the members joining the cluster, establishing the cluster structure is complete, and at the same time, the cluster head sets the energy threshold in the cluster according to its current remaining energy:

$$E'_{threshold} = P\left(E_n - \alpha \times E_{Inception}\right) \quad (10)$$

Here, α represents a constant between 0 and 1, $E_{Inception}$ represents the initial energy of a node, and E_n represents the remaining energy of the cluster head.

2.2.2.2.3. Establishing the routing

Establishing the wireless sensor routing for transmitting and collecting agricultural planting temperature data is divided into 2 processes: intracluster routing and the intercluster routing tree. In this paper, time division multiple access (TDMA) was used to complete the communication of the multinode temperature data of the agricultural planting in the cluster, which can effectively avoid message conflict when nodes in the cluster transmit agricultural planting temperature data. The cluster head creates a TDMA schedule and allocates the time slots of the cluster members. The nodes in the cluster can only send real-time planting area temperature data to the cluster head in their own time slots. When each TDMA frame is completed, the cluster head will fuse the agricultural planting temperature data it receives and send it to the sink node. In the stage where the cluster is established, each wireless SN keeps a neighbor cluster head table, so the cluster head node can select the next hop agricultural planting temperature data transmission position according to the neighbor cluster head table, and through this route, it is in the first place, the next hop of the cluster head of layer, l, is the aggregation node of the whole WSN. Finally, an intercluster routing tree, with the sink node as the root node, is established to complete the routing establishment of the cluster, as shown in Figure 3.

2.3. Digital agricultural planting multinode temperature abnormal monitoring

2.3.1. Monitoring efficiency optimization for temperature abnormalities

After the temperature data is transmitted to the target device, the data needs to be processed and analyzed to get information about abnormal temperatures. However, the processing and analysis process is complicated and time-consuming, and there is a delay, which leads to a long response time for the temperature anomaly monitoring. Therefore, in order to better monitor the temperature in the planting area, multiple input multiple output (MIMO) technology should be implemented in the multinode temperature data transmission of the agricultural planting between 2 adjacent cluster heads to maximize energy saving, and cooperative nodes should be carefully selected between 2 directly adjacent cluster heads with temperature data communication behavior to improve the efficiency and response speed of the temperature anomaly monitoring.

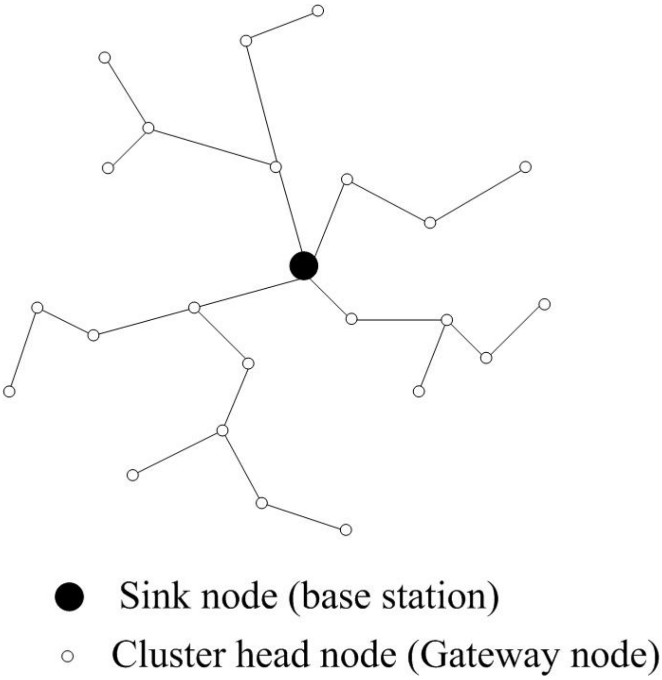

Figure 3. Routing tree between the wireless sensor clusters.

In order to explain this strategy, the following assumptions are made: the current cluster head adopts the MIMO technology and uses S_{co} cooperative nodes to transmit the environmental temperature data of the crops to the neighboring cluster heads CH_n; the intracluster communication is an additive white gaussian noise (AWGN) channel model, and the communication energy is proportional to the square of the path loss. Communication of the temperature data between the clusters is further and more complicated than the communication within clusters in terms of the distance and communication environment, so it is assumed to be in flat Rayleigh fading channel mode. The modulation mode of the signal is binary phase-shift keying (BPSK), and the bandwidth is *B* Hz.

In this research, d_{i_ch} represents a node, $i(i \in S_{co})$, and the cluster head node to which it belongs, $d_{i\_CH_n}$ and *k*, respectively, represent the distance and path loss parameters of node, *i*, and reach the adjacent cluster head, CH_n. The single hop communication process between cluster heads is divided into 2 steps:

Step 1: The current cluster head broadcasts the temperature data to a plurality of cooperative nodes.

Step 2: The cooperative node encodes the planting environment temperature data in orthogonal space time block codes (STBC) and forwards them to the destination cluster head, CH_n.

The multinode temperature data transmission mode of the agricultural planting in MIMO-HEED mode is shown in Figure 4.

(1) Energy consumption of the intercluster temperature data communication

$E_{bt}(inter)$ represents the energy consumption value of the intelligent temperature data transmission between the clusters using MIMO technology. The link between each cluster is assumed to be a flat Rayleigh fading channel. In the BPSK modulation mode, the communication energy consumption required to send each bit can be approximately expressed as shown in Eq. (11):

$$E_{bt}(inter) = \frac{E'_{threshold}(1+\alpha)N_0\left[(G_t G_r \lambda^2)M_l N_f + S_{op}\right]}{P_b^{\frac{1}{S_{op}}} B^2 d_{i\_ch}^k} \quad (11)$$

Here, α represents the efficiency value of the *RF* amplifier, N_0 represents the spectral density of noise energy on one side, *Gt* and *Gr*, respectively, represent the antenna gains of the transmitter and the receiver, λ represents the wavelength of the carrier wave, S_{op} indicates the number of cooperative nodes, P_b is the approximately equal e^{-r}, so there is $P_r = -2BN_f\sigma^2 ln(P_b)$, P_r receives the energy value of the planting environment temperature data, σ^2 is the energy density of AWGN channel, and N_f is the noise value of the receiving end; assume that when data is transmitted in a cluster, the path loss parameter $k = 2$, and M_l represents the link richness.

(2) Energy consumption of the temperature data collected by the clusters, $E_{intra}(N_c)$.

Communication of the temperature data in the cluster is an AWGN channel model, and the energy of the intelligent

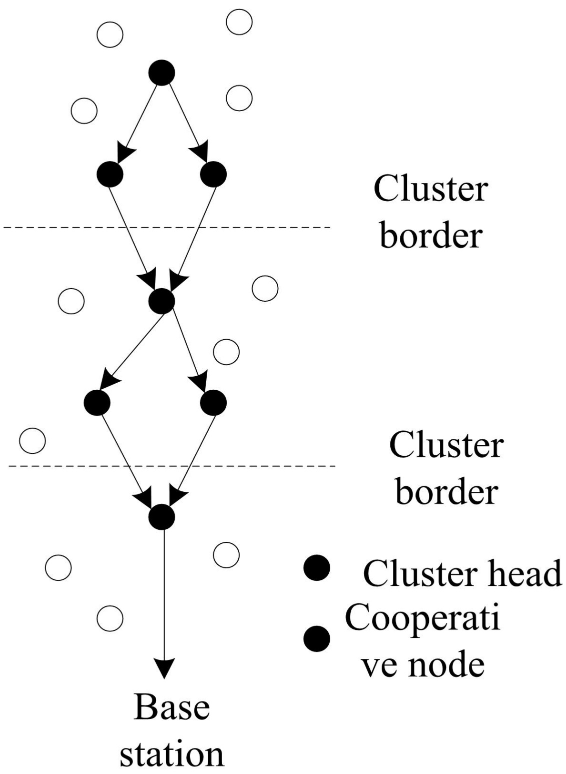

Figure 4. Multihop MIMO mode.

communication of the temperature data is proportional to the square of the path loss. The energy consumption of the member nodes in the cluster to send 1 bit of planting area temperature data to the cluster head is $E_{intra}(N_c)$, where N_c is the optimal number of clusters, as shown in Eq. (12):

$$E_{intra\_bt}(N_c) = \frac{BE_{bt}(inter)}{-2(1+\alpha)N_f\sigma^2 ln(P_b)GE[d_c^2]M_l + S_{op}} \quad (12)$$

Here, d_c is the distance from the member node to the cluster head. The average number of member nodes in each cluster can be expressed as $[M/N_c]$, the sum of all of the bits sent by the member nodes to the cluster head in each cluster is $S_1(N_c) = [M/N_c]F_nP_s$, so we end up with $E_{intra}(N_c) = N_cS_l(N_c)E_{intra\_bt}(N_c)$.

(3) Energy consumption of the cooperative nodes sending temperature data to the cluster heads, $E_{co\_CH}(N_c, S_{op})$. In the cooperative node of the current cluster head, S_{op}, before transmitting the temperature data to the next hop cluster head, the temperature data are encoded by orthogonal STBC and become STBC symbols. This process must consider the extra cost caused by the training process in communication. Suppose there is a set of STBC symbols with the size of *F*. These include pS_{op} training symbols, and the group of symbols in *K* is sent by the cooperative node within symbol time, then, the symbol sending rate is$R = \frac{F}{K}$. Therefore, the cooperative node transmits the received size to the next hop cluster head, $S_2(N_c)$.When the temperature data of the bits are grouped, the actual amount of temperature data sent is. Therefore, the energy $S_e(N_c, S_{op}) = FS_2(N_c)/\,R(F - pS_{op})$ consumption of the cooperative node sending the temperature data to the cluster head, $E_{co\_CH}(N_c, S_{op})$, can be expressed as given in Eq. (13) below:

$$E_{co\_CH}(N_c, S_{op}) = \frac{BS_e(N_c, S_{op})\left[\frac{(1+\alpha)S_{op}N_0}{P_b^{\frac{1}{S_{op}}}}\right]}{(G_tG_r\lambda^2N_c) + S_{op}}[(8L)^2\pi_lN_f] \quad (13)$$

On the basis of the above analysis, the total energy consumption of the network in each round of planting area temperature transmission, $E(N_c, S_{op})$, can be obtained using Eq.(14) below:

$$E(N_c, S_{op}) = E_{intra}(N_c) + E_r(N_c) + \overline{n_h}\left(E_{CH\_co}(N_c, S_{op}) + E_{co\_CH}(N_c, S_{op})\right) \quad (14)$$

Here, $\overline{n_h}$ represents the average hop number of the temperature data in the network reaching the sink. To simplify the analysis, it is assumed that the formula $\overline{n_h} = N_c$ holds, which means that the average number of hops is exactly equal to the number of clusters distributed on the edge of digital agricultural planting perception area. When constructing the optimal energy consumption model, the optimal value of the following optimization

problems are used to solve the number of cluster heads, N_c, and the number of cooperative nodes, S_{op}:
$(N_c^*, S_{op}^*) = argmin\, E(N_c, S_{op}) s.t. S_{op} \leq 10, N_c \ll \frac{M}{3}$ (15)
Here, the first restriction means that with the increase of the cooperative nodes, although the energy consumption of the temperature data transmission can be reduced, the energy consumption of the circuit is also increased, so the number of cooperative nodes is limited. The second constraint limits the size of each cluster. Because the range of the values of N_c and S_{op} is limited, and the optimal solution of the optimization problem of Eq. (15) can be obtained via the exhaustive method.
To sum up, through optimization of the temperature data transmission protocol of the WSN, the effect of obtaining the digital results of the multinode temperature data of the agricultural planting by the WSN is improved, the energy consumption of the temperature data collection is reduced, and the efficiency of the temperature anomaly monitoring is improved.

2.3.2. Realization of temperature anomaly monitoring

Based on the multinode temperature data of the digital agricultural planting collected by the WSN and transmitted to the upper computer, the multinode temperature of the digital agricultural planting of 40 is taken as the abnormal threshold for monitoring to obtain the multinode temperature data of abnormal digital agricultural planting, and then the waveforms composed of 20 consecutive temperature collections under abnormal conditions are selected as abnormal temperature samples respectively, and the characteristics of the abnormal sample temperature waveforms are extracted from them, and used as the input data of the Bayesian classifier for training, where the temperature value collected in real time is input into the Bayesian classifier to monitor the temperature anomaly and determine the type of temperature anomaly it is. This method is shown in Figure 5.
According to the sample temperature characteristic values of the high temperature alarm, low temperature alarm, and normal state, set $S = 0$ indicates a low temperature alarm, $S = 1$ indicates a normal state, and $S = 2$ indicates a high temperature alarm. Among them, num_c samples are collected by the low temperature alarm, num_a samples are collected by the normal state, and num_r samples are collected by the high temperature alarm, each of which is a collection of 20 temperature data. The number of samples in the 3 cases accounts for the total number of samples, as shown in Eqs. (16) to (18):

$$P(S = 0) = \frac{num_c}{num_c + num_a + num_r} \quad (16)$$

$$P(S = 1) = \frac{num_a}{num_c + num_a + num_r} \quad (17)$$

$$P(S = 2) = \frac{num_r}{num_c + num_a + num_r} \quad (18)$$

Taking $S = 1$ as an example, the other 2 cases are handled in the same way. The corresponding 5 feature values are extracted for num_a samples, and the number of each feature value is . Then, each feature value is divided by g_i as the gradient. The division gradient is shown in Eq. (19):

$$g_i = \frac{CV_{i\_max} - CV_{i\_min}}{n}, i \in [1,5] \quad (19)$$

Here, CV_{i_max} is the maximum in the ith eigenvalues, CV_{i_min} is the minimum in the ith eigenvalues, n is the number of intervals that divide the eigenvalues, and the divided intervals are expressed as $R_j, j \in [1, n]$.
To calculate the proportion of eigenvalues of the 5 samples in each interval, R_j, take the mean T_{avg} of $S = 1$ as an example, the other 4 eigenvalue processing methods are consistent, totaling a num_a mean value. Use set $Avg = \{T_{avg\_1}, T_{avg\_2}, \cdots, T_{avg\_num_a}\}$, R_j to express where the number of the mean value in the interval, R_j, is num_j. The proportion of the mean value in the interval, R_j, is shown in Eq. (20):

$$P(Avg \in R_j | S = 1) = \frac{num_j}{num_a} \quad (20)$$

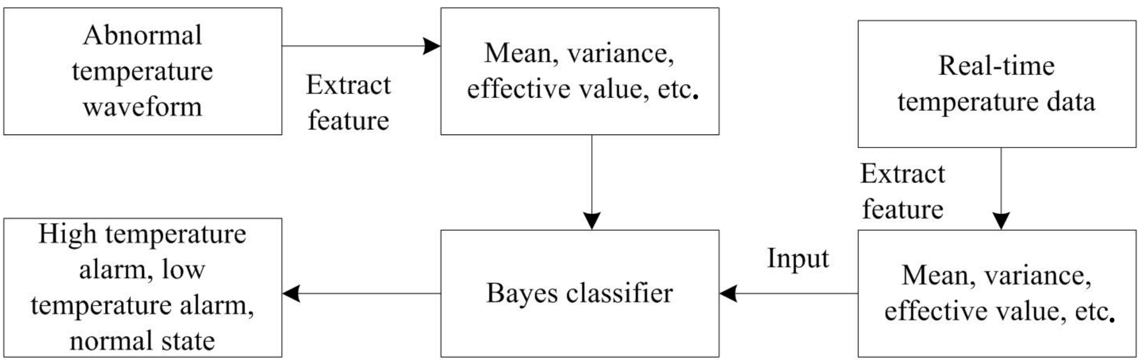

Figure 5. Abnormal situation determination classification.

In the above process, the prior probability is calculated according to the samples of 3 situations, and the calculation process is completed on the computer. Then, the real-time temperature data collected by the SNs are uploaded to the computer, and finally, the real-time temperature data are examined and classified using the prior probability, so that the temperature is too high or too low for the early warning. When the sensor network prompts the high temperature warning, it is necessary to combine watering, irrigation, and greenhouse ventilation in order to cool the temperature in the greenhouse down. When the sensor network prompts the low temperature warning, it is necessary to increase the heater temperature and turn off the ventilation equipment to increase the temperature in the greenhouse. Therefore, the multinode temperature monitoring of digital agricultural planting based on the WSN is realized.

3. Experimental analysis

3.1. Experimental setup

In order to verify the practical application effect of the method in this paper, the experiment was carried out in a digital agricultural planting greenhouse located in a certain area of L Province. The digital agricultural planting greenhouse mainly grows vegetable crops, and it uses computer technology, communication and network technology, and automatics. High-tech technologies such as scientific management and professional opinions put forward by agrobotany experts are used to monitor crops in the production process to ensure crop growth and improve crop yield and quality.

The temperature of the greenhouse should be controlled to between 15 and 25 ^{O}C to ensure the normal growth of vegetable crops. In order to ensure the complete coverage of SNs in the greenhouse, a total of 300 DS18B20 digital temperature sensors were used, and the sensors were connected to the Arduino to read the sensor data and send it to the WSN. The Azure platform was chosen for the data processing, and then the sensor data were visualized through Matplotlib, which provided real-time monitoring and analysis functions. The experimental environment is shown in Figure 6.

3.2. Experimental analysis

In order to ensure accuracy of the temperature collection by the sensors and reduce the errors caused by equipment, 10 temperature sensors out of 300 were randomly selected for temperature collection and testing. The sensors were placed in an environment between 15 and 25 ^{O}C, and the temperature was increased by 5 ^{O}C every 30 min. The measurement results are shown in Table 1.

As can be seen in Table 1, the maximum error of the data collected by the 10 sensors was 0.4° at the standard temperature of 15 to 25 ^{O}C Within the standard error of the sensors, the temperature data collected by this sensor can be considered as standard temperature data. They play a great role in the accuracy of digital agricultural planting temperature monitoring.

Figure 6. Experimental environment.

Table 1. Sensor test results.

Sensor number	Standard temperature, ^{O}C		
	15	20	25
1	15	20.1	25
2	15	20	25
3	15	20.2	24.7
4	15.1	19.8	25
5	15.3	20	25.3
6	14.8	20.3	25.2
7	15	20	25
8	14.8	20	25.2
9	15	20	24.9
10	15	20.3	25

The method in this paper was used to optimize the transmission of the collected temperature data and compare it with the low-energy adaptive clustering hierarchy (LEACH) and HEED (a hybrid) transmission protocols. The survival ratio of the WSN nodes in a certain period of time and the relationship between the number of data received by the BS and energy consumption were compared, respectively. The results are shown in Figures 7 and 8.

As can be seen in Figures 7 and 8, the LEACH method had a larger percentage of nodes surviving before 88×10^3 than that of the HEED method, but the survival ratio of the nodes after this time was smaller than that of the HEED method. However, in the relationship between data transmission times and energy consumption, the energy consumption of the LEACH method to transmit the same number of data was greater than that of the HEED method, but the improved data transmission protocol of this method can guarantee the survival time of the nodes to the greatest extent and send data to the BS with the least energy consumption.

The content of the control interface displayed by the upper computer after the collected agricultural planting temperature data were uploaded to the upper computer is shown in Figure 9.

In the display and control interface of the upper computer, it can control the sensors to collect and upload temperature data, display the real-time uploaded temperature data of different SNs, save the current temperature data uploaded by the temperature sensors, check the temperature data uploaded by the sensors in the past, and set the upper and lower limits of the alarm temperature. When the temperature data exceeds this value, it will give an alarm and display an abnormality in the control interface. At the same time, it can set the on and off of the alarm switch.

In order to verify the practical application effect of the method in this paper, the upper and lower alarm temperatures were set to 15 and 25 ^{O}C, respectively, and the temperature was raised above and below 25 ^{O}C manually. If the alarm was triggered, the temperature was controlled. The experimental results are shown in Table 2.

As can be seen in Table 2, this method will sound an alarm in real time when the temperature is abnormal, and inform the management personnel to control the temperature in real time, and stop the alarm when the temperature changes and reaches the set safe temperature range. It can be seen that the practical application effect of this method was very strong.

The accuracy of the temperature anomaly monitoring was compared using the proposed method, a monitoring method for seed germination and growth characteristics under electromagnetic radiation (Khashayarfard et al., 2023), the Internet of Things and Arduino Uno method given by Mohammed et al. (2022), and the corn field temperature and humidity monitoring method based on the WSN reported by Li et al. (2020), and the results are shown in Figure 10.

Analyzing Figure 10, it can be seen that when using the proposed method for temperature monitoring, the monitoring accuracy remained above 96%, which is higher than that reported by Khashayarfard et al. (2023), Mohammed et al. (2022), and Li et al. (2020). In regard to the accuracy of the 3 comparison methods, that of Khashayarfard et al. (2023) was about 95%, that by Mohammed et al. (2022) was about 94%, and that of Li et

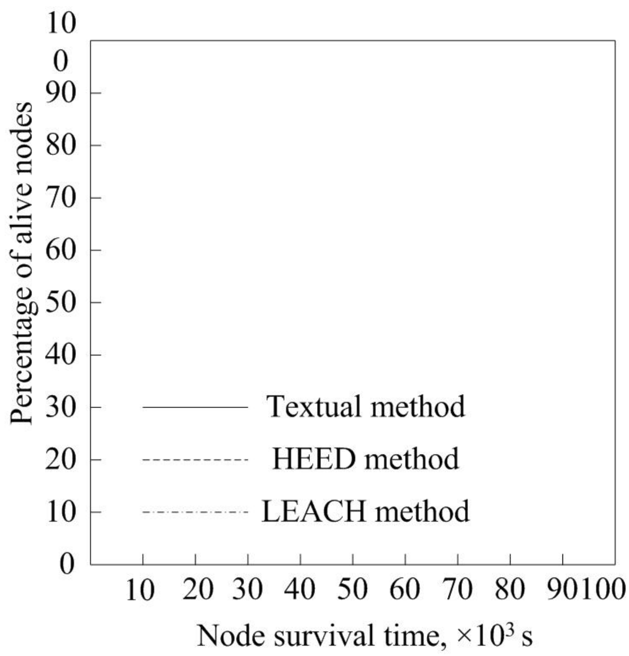

Figure 7. Comparison of the WSN node survival time.

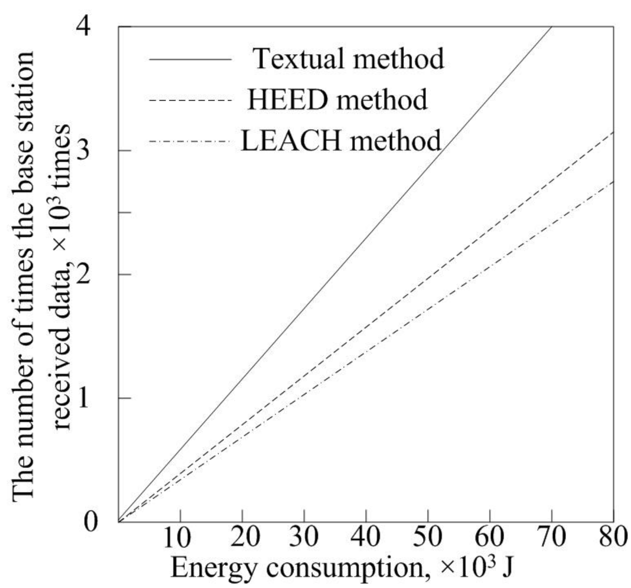

Figure 8. Relationship between the amount of data received by the BS and energy consumption.

al. (2020) was about 93%. This indicates that the proposed method can achieve accurate monitoring and control of the temperature at multiple nodes in digital agricultural planting. By utilizing WSNs, feature extraction, data transmission, MIMO mode, and temperature anomaly monitoring algorithms, high monitoring effectiveness can be achieved, and timely temperature anomaly alarms and corresponding temperature control strategies can be provided to improve the efficiency and yield of agricultural planting.

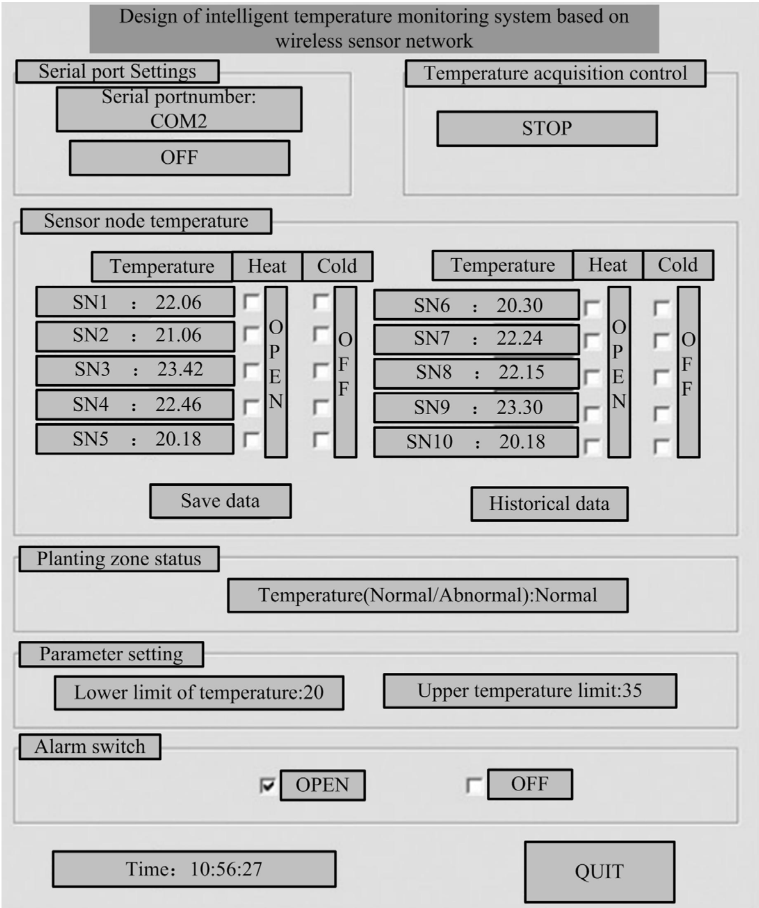

Figure 9. Display and control interface of the upper computer.

Table 2. Temperature monitoring results.

Exception number	Time	Abnormal temperature, ^{O}C	Alarm or not	Intervention temperature, ^{O}C
1	5:24–8:15	25.3	Yes	20
2	5:25–11:27	25.5	Yes	21
3	5:25–22:07	16	No	16
4	5:26–10:01	28.8	Yes	18
5	5:26–14:50	32.5	Yes	24
6	5:26–20:30	14.7	Yes	16
7	5:27–9:03	15.5	No	15.5
8	5:27–13:15	30	Yes	22.8
9	5:27–23:00	17.8	No	17.8
10	5:28–8:00	26	Yes	19

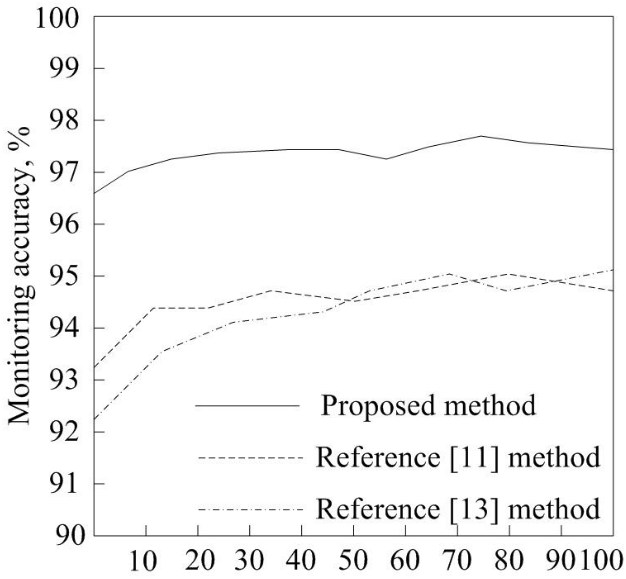

Figure 10. Accuracy of the temperature anomaly detection.

4. Conclusion

In order to improve the efficiency of multinode temperature monitoring of agricultural planting, this paper proposed a multinode temperature monitoring method of digital agricultural planting based on WSN. The experiments showed that this method can reduce the energy consumed in data transmission between nodes and maximize the survival time of the nodes, and can increase the service life of the nodes, thus reducing the cost. At the same time, it can accurately detect temperature changes, and sound an alarm when the temperature exceeds the limited threshold, which shows that the method in this paper has strong practicability and can provide great advantages in practical application.

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