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RESEARCH ON INTELLIGENT AGRICULTURE BASED ON ARTIFICIAL INTELLIGENCE AND EMBEDDED PERCEPTION ALGORITHMS

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Abstract. In order to solve the problems of weak collection link, limited data coverage and poor real-time for big data in agriculture, smart agriculture by implementing artificial intelligence and embedded sensing is proposed. The front-end perceptron and wireless gateway were designed. A steady-state data collection system was constructed according to the characteristics of intelligent agricultural information data. Combining various algorithms such as data unification and data recognition, intelligent perception calculation parameters were extracted. The adaptive steady-state sensing model was designed relying on deep learning technology in the field of artificial intelligence. The experimental results show that the RMSE value of the designed system in the study is 0.028, which meets the requirements of intelligent agricultural information data perception accuracy. It is concluded that agricultural big data is a collection of data involved in the process of agricultural production, transportation and marketing, and data collection is the most important part of it.

Key words: artificial intelligence, embedded sensing, smart agriculture

1. Introduction and examples. The development of artificial intelligence in agriculture has changed people's thinking about agricultural management services. Based on the background of big data, the reasonable use of artificial intelligence can effectively monitor the production of agricultural products and build a management system that combines information monitoring and services. The system has the functions of early warning of natural disasters, prevention and control of pests and diseases, and prediction of market fluctuations, which effectively reduces the construction of agricultural platforms and creates new engines and dynamics of agricultural and rural modernization [1]. Intelligent agriculture refers to an agricultural model that utilizes modern technological means to improve agricultural production efficiency and agricultural product quality. Among them, the application of artificial intelligence and embedded perception technology can greatly improve the efficiency and intelligence level of agricultural production.

In order to accelerate the construction of digital agriculture, we should not only play the role of the government, but also mobilize the strength of all parties to form a joint effort to promote it. We should encourage and guide social capital to invest in agriculture and broaden the source of funds for agricultural and rural development. In accordance with the digital construction carried out by agricultural enterprises and new business entities, it is recommended that the government introduce relevant support policies to provide financial incentives to accelerate the process of digital platform construction. We should strengthen the construction of agricultural infrastructure, actively carry out the creation of modern agricultural parks, and fundamentally improve the conditions of agricultural practices. We should strengthen digital agriculture and rural business training, carry out digital agricultural talents to the countryside, popularize digital agriculture-related knowledge, digital technology application and management level of new business entities and high-quality farmers. We should play the role of scientific research institutions, universities, enterprises and other parties to speed up small farmers and digital agriculture interface, and accelerate the integration and application of agricultural data. At the same time, we should use digital technology to transform traditional industries in the countryside, attract outstanding urban talents to return to their hometowns for employment and entrepreneurship, inject new ideas, new thinking and new strategies into agricultural production, guarantee the scientific nature of agricultural business decisions, and further promote the high-quality development of digital agriculture [2,3].

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2. Literature Review. With the Internet of Things, big data, artificial intelligence and other technology applications continue to sink into the social life of production practices, digital agriculture has become the focus of the development of the agricultural industry now and in the future. Artificial intelligence can improve the accuracy and speed of agricultural production decision-making by analyzing a large amount of agricultural data. For example, using machine learning algorithms to analyze and predict agricultural data can predict crop growth periods, diseases and pests, and take timely measures to protect crops and improve crop yield and quality. The deepening of the application of digital agriculture in China's agricultural production prompts significant changes in China's traditional agricultural production methods. More and more crude, mechanical and empirical production modes are developing towards intensive, intelligent and scientific. Today, digital applications have become the mainstream of industrial production and social life, while the application of digital technology in agricultural production is still in its infancy. The agricultural sector may be the last industry where information technology and digitalization are popularized. The reasons for the slow diffusion of digital technology applications in agriculture are multi-layered, the main reason of which is that the scattered production and operation mode in rural areas of China is not conducive to the concentration of data resources in the informatization system [3]. And with the continuous improvement of rural communication infrastructure, the gradual maturity of agricultural IoT technology, and the national vigorous promotion of the construction of modern agricultural industrial parks, data integration in the whole agricultural industry chain has become possible. Liu, S. et al. constructed an agricultural Internet of Things (IoT) management system to realize the integrated management of Internet devices, environmental data, video data and agricultural expert knowledge. Then, they introduced the current status of agricultural IoT from the perspective of sensing technology, transmission technology and three intelligent information processing technologies, analyzed the economic benefits of IoT for agricultural production, and proposed future research priorities and development directions for agricultural Internet in China [4]. Vermesan, O. et al. introduced ECAS vehicles through artificial intelligence (AI) in vehicle and infrastructure-level architectures based on evolution of distributed intelligence based domain controllers, regional vehicles and federal vehicle/edge/cloud centers, and the role of AI technologies and approaches in achieving different autonomous driving and optimization functions for sustainable green transportation [5].

Agricultural big data is the overall collection of data involved in the process of agricultural production, transportation and sales, and data collection is prominent as its most important link. Embedded perception technology can achieve real-time monitoring and data collection of agricultural production environment, such as temperature, humidity, lighting and other environmental factors. At the same time, it can also achieve real-time monitoring of crop growth, such as crop growth status, pests and diseases. These data can be used to improve the accuracy of agricultural production, thereby reducing waste and improving agricultural efficiency. In the early days, the degree of agricultural informatization was low, agricultural data was small and the mining value was low. However, in recent years, the development of agricultural artificial intelligence and embedded sensing technology has made agricultural data show a spurt growth. Although the current development of agricultural big data is a big improvement over the previous, there are still some problems in the data collection link:

1. The data collection in agricultural production is uneven, only in the more developed areas of communication, and data transmission is mainly wired network;
2. The data collection is mainly based on sensor text information, with less image and video information;
3. The cost of the existing intelligent agricultural monitoring system is high and the system integration is low, it is not applicable to areas where broadband is not laid, and it is difficult and costly to deploy.

By summarizing the previous research experience, artificial intelligence technology is adopted in this study to establish an embedded sensing system with artificial intelligence adaptive sensing model as the focus to realize the sensing of agricultural information.

3. Method.

3.1. Front-end perceptron design for artificial intelligence-based embedded sensing system for agricultural information. In order to realize the collection and transmission of agricultural information, the front-end perceptron is designed. The agricultural information embedded sensing system of artificial intelligence is a system that applies modern sensing technology, communication technology, computer technology, and artificial intelligence technology to the agricultural production process. The front-end perceptron is an important component of the system, mainly responsible for collecting various parameter information in the

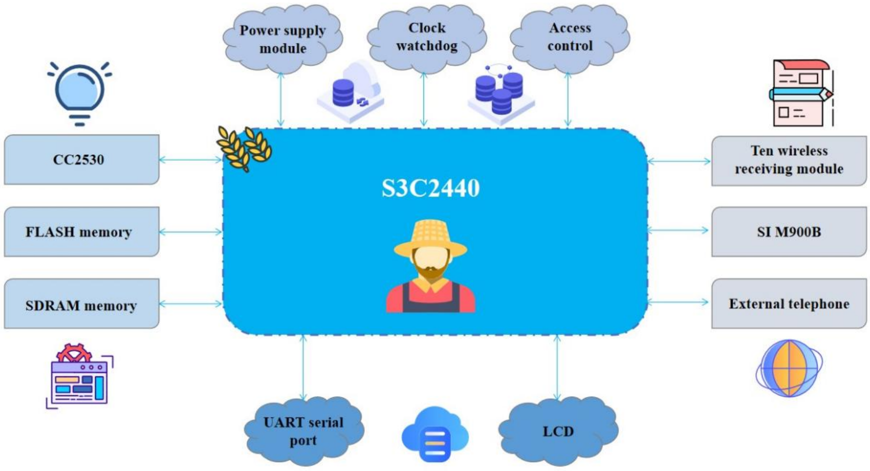

Fig. 3.1: Block diagram of the hardware structure of the gateway

agricultural production process and transmitting this information to the backend data processing center for processing and analysis. Considering the node power consumption and information reception sensitivity degree, the front-end sensing device designed in the study uses the CC2530 chip as the core, and connects the CC2530 chip to the microcontroller I/O port for the purpose of information exchange. Then it is combined with wireless transceiver module, clock module and other structures to complete the front-end sensing device design [6].

3.2. Wireless gateway design for artificial intelligence-based agricultural information embedded sensing system. The wireless gateway is designed mainly for data transmission, encapsulation and parsing. Through research, it is known that the S3C2440 microprocessor can operate at a maximum frequency of 400MHz, which can meet the working requirements of the sensing system. In this study, it is used as the design core of the wireless gateway, and then it is connected with components such as TFT-LCD display and remote control keypad. The actual hardware structure of the wireless gateway is shown in Figure 3.1.

In addition to the hardware structure of the gateway shown in Figure 3.1, the LM25965-5.0 switching voltage regulator is installed at the gateway power supply in order to enhance the stability of the gateway application.

3.3. Building intelligent agricultural information data collection system. The sensing of smart agriculture information needs to be based on data. The data collection structure of smart agriculture information shown in Figure 3.2 is designed in the study. The construction of an intelligent agricultural information data collection system requires consideration of multiple aspects, including the selection and configuration of hardware equipment, the design and implementation of data collection methods, data storage and processing, data display and analysis, etc.

In the acquisition structure shown in Figure 3.2, S denotes the data collector, C denotes the encoder, $l_1 and L_2$ denotes the channel length. In order to ensure the integrity of steady-state data acquisition, an in-depth analysis is conducted for the two phases of information transmission, and the acquisition information of a single data concentrator is clarified, and the acquisition information is calculated by the coding function to generate the input signal. A moment in the data acquisition structure shown in Figure 3.2 is selected, and the data acquisition channel is described by Equation 3.1.

$$Y_a = X_{ja} + Z_a, Z_a \in N \tag{3.1}$$

In Equation 3.1, X denotes the input signal, Y denotes the output signal, a denotes the acquisition moment,

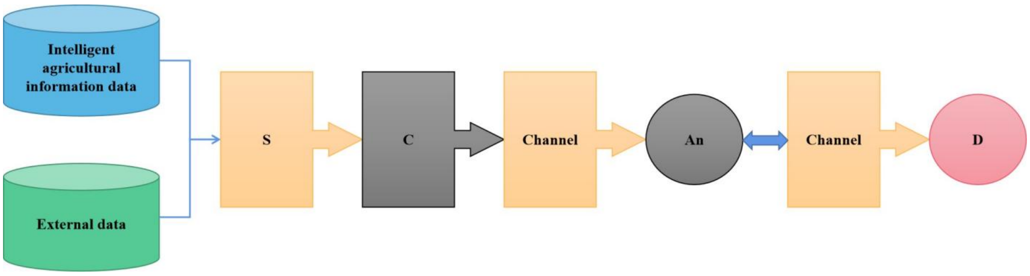

Fig. 3.2: Structure of intelligent agricultural information data collection

m denotes the number of data acquisition points of intelligent agricultural information, and denotes a data collection point, Z denotes interference noise, and N denotes variance [7,8].

Setting the critical capacity of the channel to transmit information in line with the minimum coded transmission requirements, the channel upper limit is calculated as Equation 3.2.

$$Q = L_1 \sum_{j}^{m} log(1 + \frac{P_j}{N_j}) + L_2[log(1 + \frac{P_f}{N_f}) + log(1 + \frac{P_Z}{N_Z})] \tag{3.2}$$

In Equation 3.2, Q denotes the upper limit of the channel, $P_j P_f P_z$ denotes the average noise power of the information transmission process, $N_j N_f N_s$ denotes the noise variance of the information transmission process. For each average noise power analysis, the power constraint of each information transmission stage can be derived.

$$\begin{cases} P_j \geqslant \frac{1}{n} \sum\limits_{a=1}^{n} [X_{j1}(w_j, a)]^2 \\ P_f \geqslant \frac{1}{n} \sum\limits_{i}^{n} (X_{12}, ..., X_{m2}, i)^2 \\ P_z \geqslant \frac{1}{n} \sum\limits_{i}^{n} Z_i^2 \end{cases} \tag{3.3}$$

In Equation 3.3, ω indicates the agricultural information state quantity. Combining with the constraints shown in Equation 3.3, the spacing of the front-end data collectors in the steady-state data collection structure is set to realize the overall collection of steady-state data.

3.4. Extraction of intelligent perception calculation parameters. Based on the results of agricultural information data collection, techniques such as data unification and data recognition are applied to extract the mainstream features of steady-state data. Considering that the collected data are associated with both time and space, a data unification multi-layer model is designed in the study to identify the data states. Each feature quantity for the collected steady-state data is recorded to form the following matrix.

$$D = \begin{bmatrix} d_{11} & ... & d_{1\alpha} \\ . & & . \\ . & & . \\ . & & . \\ d_{\beta 1} & ... & d_{\beta z} \end{bmatrix} \tag{3.4}$$

In Equation 3.4, D denotes the acquisition matrix, d denotes the number of individual features of the acquisition data, $\alpha\beta$ denotes the number of columns and rows of the acquisition matrix.

$$\widetilde{\omega}_\alpha = (v_1, v_2, ..., v_\alpha) \tag{3.5}$$

In Equation 3.5, $\widetilde{\omega}$ denotes a sequence of steady-state data vectors, v denotes the matrix column vector.

Considering that the frequency of steady-state data collection varies, some of the collected data have the problem of loss. In the study, a dynamic time programming method is used to calculate the similarity of discrete sequences, and complete the sequence expansion and compression to ensure the uniformity of the sequence scale. A column vector is randomly selected as the reference vector within Equation 3.5, and the Euclidean distances of other column vectors are calculated to generate multiple distance matrices.

$$O_k = \begin{bmatrix} B_{11} & ... & B_{1\beta} \\ . & & . \\ . & & . \\ . & & . \\ B_{\beta 1} & ... & B_{\beta\beta} \end{bmatrix} \tag{3.6}$$

In Equation 3.6, k denotes the column vector, O_k denotes the distance matrix, B denotes the Euclidean distance. The distance matrix is extrapolated to form several distance loss matrices to complete the calculation of the column vector similarity.

$$\theta = \begin{bmatrix} \varepsilon_{11} & ... & \varepsilon_{1\beta} \\ . & & . \\ . & & . \\ . & & . \\ \varepsilon_{\beta 1} & ... & \varepsilon_{\beta\beta} \end{bmatrix} \tag{3.7}$$

$$Q = \{Q_1, Q_2, ..., Q_\beta\} \tag{3.8}$$

In Equation 3.7 and 3.8, θ denotes the distance loss matrix, ε denotes the degree of loss, and Q denotes the optimally adjusted sequence and also the set of shortest paths within the matrix. The distance between the steady-state data vectors is adjusted by dynamic regularization techniques to ensure the distance minimization.

Then, using principal component analysis, the validity of the steady-state data is evaluated, duplicate redundant information is removed, and the complexity is calculated. First, the normalization process is performed for the adjusted vector distances to obtain the normalization matrix shown below.

$$U = \xi - \frac{\xi}{\beta} \tag{3.9}$$

In Equation 3.9, U denotes the normalized matrix and ξ denotes the interval distance adjusted covariate data, and based on the calculation of Equation 3.9, the covariance matrix and singular value decomposition formulas are obtained as follows.

$$E = \frac{1}{\beta} U \tag{3.10}$$

$$svd(E)[H, R, F] \tag{3.11}$$

In Equation 3.10 and 3.11, E denotes the covariance matrix, svd denotes the singular value decomposition, H, R, F denotes the matrix formed after decomposition, H denotes the dimensionality reduction matrix, and the main data vectors are dimensionally reduced by using the dimensionality reduction matrix.

Relying on the above dimensionality reduction data, the intelligent perception parameters of a single sample are calculated in combination with support vector machines, and then the likelihood functions of the unknown parameters are calculated with reference to the independence of each observed object within the collection sample. In summary, the extraction of intelligent perception computational parameters is completed [9].

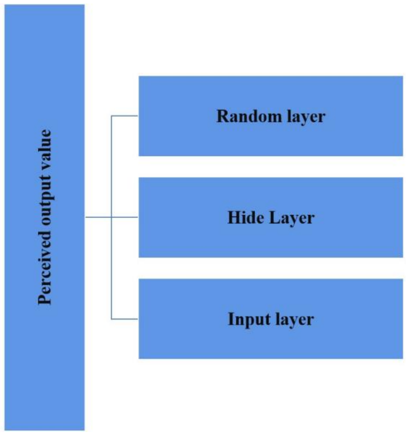

Fig. 3.3: Artificial intelligence-based adaptive perception model

3.5. Building an artificial intelligence adaptive perception model. The embedded sensing system designed in the study is centered on artificial intelligence technology, i.e., an artificial intelligence adaptive perception model is used as the focus of the research, and deep learning techniques within the field of artificial intelligence are applied to construct an adaptive perception model. The adaptive perception of the steady-state action behavior is divided into two parts, on the one hand, the input to output calculation of the AI neural network, and on the other hand, the parameter weights are modified based on the output perceived posture values. Deep learning technology is a machine learning method based on artificial neural networks. Its main feature is that it can automatically learn and extract features from data, and thus construct more accurate and efficient models. In embedded sensing systems, deep learning technology can be applied to the construction and optimization of perception models. By training and learning the data collected by sensors, more accurate and adaptive perception models can be constructed, improving the perception accuracy and stability of the system.

The adaptive perception model relying on artificial intelligence technology consists of four main layers of structure, as shown in Figure 3.3.

According to the schematic diagram of the perception model shown in Figure 3, it can be seen that the input layer includes the current steady-state condition of intelligent agricultural information, and according to the two parameters mentioned above, the input vector is described as:

$$\lambda(t) = (\lambda_1(t), \lambda_2(t), ..., \lambda_2(t)) = \{\rho(t), \rho(t-1), ..., \rho[t-(\partial-1)\tau]\} \tag{3.12}$$

In Equation 3.12, $\lambda(t)$ denotes the input vector of the perceptual model in time input vector, ∂ denotes the attack time interval, ρ denotes the steady state condition of agricultural information data, τ denotes the time delay.

The information of the input layer of the adaptive perception model is passed to the hidden layer, which is computed via multiple hidden nodes to obtain.

$$\mu(t) = \frac{1}{1+\psi^r} \tag{3.13}$$

In Equation 3.13, μ denotes the hidden layer output result, ψ denotes the constant, and r denotes the parameter weights.

The output results of the hidden layer are applied to the random layer to calculate the Gaussian distribution characteristics of the steady-state data as a way to describe the distribution of the output data. Considering the results of Gaussian distribution calculation for each hidden node, which is directly influenced by the intelligent perception parameters, the random layer output is expressed as:

$$\eta[\mu(t), r_0] = \frac{1}{1+\psi^{\mu(t)r_0}} \tag{3.14}$$

In Equation 3.14, η denotes the random layer output result, r_0 denotes the hidden node parameter weights.

Finally, an adaptive reinforcement learning mechanism is added to the output layer to further analyze the output results of the stochastic layer, which is expressed as a one-dimensional Gaussian function. The steady-state perception results are obtained using intelligent perception calculation parameters, and then adaptive learning is performed for the deviations in the stochastic layer to update the parameter weights and obtain more accurate adaptive perception results for the steady-state operational behavior.

3.6. Developing the embedded sensing system. After the software design is completed, an embedded real-time operating system is used for software development. Its main feature is that it can respond to external events in real-time, while ensuring that the system can complete the processing of events within a specific time range. The application of embedded real-time operating system divides the software development into several subtasks and ensures that each subtask is responsible for the corresponding responsibilities and gives each subtask the corresponding operation order.

Considering that the perception system designed in the study is an embedded operating system, a comparative analysis of commonly used embedded real-time operating systems shows that the UCOS- system has free real-time characteristics and can support more than 250 tasks to be developed simultaneously. Therefore, UCOS- is chosen as the system software development platform in the study [10-11].

Usually, embedded real-time operating systems let the tasks in the front of the operation order run first during software development and can interrupt other tasks in the operation order for CPU preemption at any time. This development model optimizes the response time of software subtask development. This development model is applied to the development of the perception system, so as to make the functional software development into task-oriented software development and realize the simplification of the logical structure of the intelligent agricultural information data perception system. Finally, the software structure is set to three layers by using the embedded real-time operating system to avoid presenting the underlying hardware directly in the visualization interface, which facilitates the expansion of software and hardware respectively. So far, the overall design of the intelligent agricultural information data embedded sensing system is completed.

3.7. System test. In the study, the artificial intelligence technology is relied on to design an intelligent agricultural information data embedded sensing system. In order to verify the practical application effect of the system, a system test is conducted. During the test, the IEEE39 node system is used as an example to apply the system designed in the study to obtain steady-state sensing results and clarify the feasibility of the system designed in the study.

3.8. Building the test environment. Considering the embedded architecture of the design system in the study, the system testing process is based on Linux system, and multiple virtual machines are used to build the system testing environment to display the perception results in a visualized form in front of the user while the intelligent agricultural information data, and the system testing environment is shown as follows. Through the establishment and testing of the system test environment, the correctness and stability of the system can be verified, and the potential problems can be found and solved in time to ensure that the system can achieve the desired effect in practical application.

Combined with seven virtual machines, the test environment is completed by using Linux Ubuntu version of the operating system and JDK version programming components. Among them, four virtual machines act as Data Node slave nodes, two act as master nodes, and the remaining one is a management node. The actual configuration information is shown in Table 3.1.

According to the configuration information shown in Table 3.1, the IP address division of the virtual machine is realized, the programming components are installed on each virtual machine separately, and the environment variables are configured after the programming software is installed.

The configuration of environment variables starts from the settings of SSH protocol and Hadoop users. First, the SSH protocol is installed in each virtual machine, and a directory with the .SSH suffix is created to facilitate subsequent system startup and command execution. Then, the SSH protocol is used to generate keyless password pairs for Hadoop users and save them in the SSH directory. Finally, after the installation of Hadoop components is completed, the core component core-site.XML and MapReduce framework files are configured to complete the address configuration of slave and master nodes [12,13,14,15]. During this test, the

Table 3.1: Virtual machine address assignment

Nodes	IP Address
CDH Management Node	192.168.155.1
CDH Primary NameNode	192.168.155.2
CDH Secondary NameNode	192.168.155.3
CDH DataNode 1	192.168.155.4
CDH DataNode 2	192.168.155.5
CDH DataNode 3	192.168.155.6
CDH DataNode 4	192.168.155.7

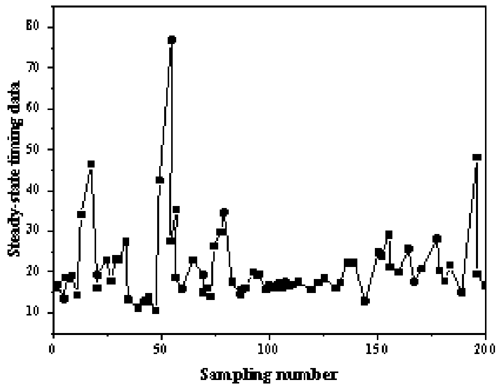

Fig. 3.4: Time-series data of agricultural information data

node system is the main result, which contains 10 generators, 46 lines and 19 load nodes in the system. In the above test environment, the sensing system proposed in the text is run to obtain intelligent agricultural information data.

3.9. Setting perceptual model parameters. In order to improve the accuracy of the test results, reasonable parameters are set for the artificial intelligence adaptive sensing model before the system is run. Running the IEEE39 node system is shown in Figure 3.4. The Nessus software is applied to scan the system acquisition characteristics, and the professional software is used to simulate network attacks during the scanning process to collect the 200 posture timing data shown in Figure 3.4.

As shown in Figure 3.4, agricultural information data can be regarded as nonlinear sequences, and agricultural information data situational awareness is accomplished by nonlinear mapping from different dimensional output spaces. Using the above 200 steady-state time-series data, 197 and 195 sets of test samples can be obtained when the dimensionality of the input vector is set to 3 and 5, respectively. The above data samples are applied to train the artificial intelligence adaptive perception model and compare the errors of the system output results under different parameters, so as to determine the final parameters of the model. It is known from the study that when the input vector dimension is set to 5, the number of nodes in the implicit layer of the model is 20, and the prediction results for the next time period of agricultural information data are more accurate [16,17,18].

4. Results and Discussion. After the parameters of the artificial intelligence adaptive sensing model are set, the embedded sensing system proposed in the study is applied to sense the steady-state operational behavior changes of the IEEE39 node system in one day, and the sensing results are combined with the actual detected state values to generate the line graph of the sensing results shown in Figure 4.1. The differences

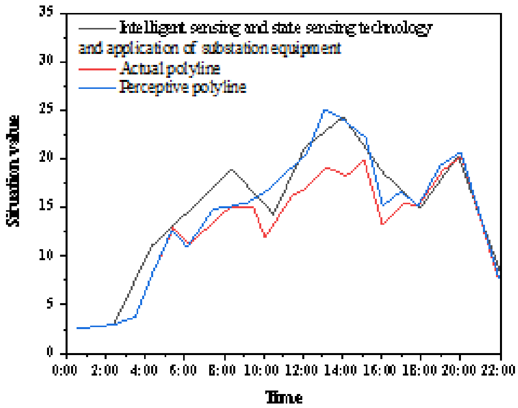

Fig. 4.1: Line graph of sensing results

between the sensed and actual data are analyzed to clarify the application performance of the designed system in the study.

According to the sensing results shown in Figure 4.1, it can be seen that, compared with the intelligent sensing and condition sensing technology and application of substation equipment, the stable posture values obtained by the sensing system designed in the study match the actual posture values in most cases, and the sensed posture is opposite to the actual posture only at ten and fifteen points. In order to describe the application effect of the sensing system more intuitively, the accuracy of the sensed posture value is calculated by using the RMSE value index in the study.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|x_i - x_i|^2} = 0.028 \tag{4.1}$$

In Equation 4.1, RMSE denotes the mean square root error, n denotes the amount of steady-state action behavior data, i denotes a sample of steady-state data, x_i denotes the actual posture value, x_i denotes the perceived potential value. According to Equation 4.1, the RMSE value of the designed system in the study is, which satisfies the accuracy requirement of intelligent agricultural information data sensing [19,20].

5. Conclusion. In this study, it is proposed to realize intelligent agriculture by implementing artificial intelligence and embedded sensing. With the advancement of artificial intelligence technology, big data analysis can be more perfect. Secondly, artificial intelligence services provide a flexible infrastructure for agricultural big data analysis, which greatly simplifies the system scale of big data analysis and can be expanded according to demand, making it easy to manage workload. Finally, artificial intelligence services make users to perform big data processing without large-scale big data resources, which greatly reduces the big data system operation costs of agriculture-related enterprises and organizations and brings great value to agricultural development. In the era of big data, artificial intelligence is the strategic direction of future agricultural development, which can effectively improve agricultural production and quality, promote agriculture in the direction of green and ecological development, and then achieve the goal of smart agriculture.

The application of artificial intelligence and embedded sensing technology in intelligent agriculture can greatly improve the efficiency and quality of agricultural production, laying the foundation for the future development of intelligent agriculture. Firstly, through the application of artificial intelligence technology, intelligent agricultural management and decision-making can be achieved. For example, using artificial intelligence technology to analyze data such as farmland soil and crop growth status, predict crop growth trends and yields, and provide more accurate and scientific decision-making basis for agricultural management. Secondly, the application of embedded sensing technology can achieve real-time monitoring and remote control of agricultural production. For example, using embedded sensors and controllers to monitor environmental factors such as weather, soil, and water quality, providing real-time feedback on data and controlling irrigation, fertilization, and other operations to improve crop production efficiency and quality.

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