Construction of a Technology System for Monitoring and Precision Maintenance of Garden Plant Growth Status Based on Internet of Things Sensing

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ABSTRACT The integration of sensing materials into garden monitoring addresses the high resource consumption and maintenance delays caused by insufficient real-time growth information and inaccurate management protocols. As wireless electromagnetic sensing and distributed communication technologies become increasingly important for intelligent environmental monitoring, this study constructs a technology system for monitoring and precision maintenance of garden plant growth based on Internet of Things (IoT) sensing. The system employs multi-source sensor nodes to collect soil moisture, temperature, ambient light, air humidity, and carbon dioxide concentration data, while a Wireless Sensor Network (WSN) enables real-time data transmission and collaborative perception. A data fusion model is adopted to extract multidimensional growth features and identify plant status, and a hybrid decision-making framework integrating fuzzy control and machine learning is developed to automatically regulate irrigation volume, fertilization frequency, and light intensity. In a pilot application in Suzhou, Jiangsu Province, the monitoring error was maintained within $\pm 2.3\%$, data latency remained below 1.5 s, the leaf area increase rate improved by 12.6%, and water and fertilizer consumption decreased by 18.4% and 16.8%, respectively. The proposed system enables dynamic perception and precision maintenance of garden plant growth while providing effective technical support for intelligent ecological management and electromagnetic sensing-assisted environmental monitoring.

INDEX TERMS internet of things sensing, wireless sensor networks, garden plant monitoring, precision maintenance, electromagnetic sensing

I. INTRODUCTION

THE parameters of the environment, climate change and maintenance procedures are some of the parameters in which the growth process of garden plants depends. Presently, urban garden management is troubled by the inability to monitor plant growth in real time and a reliance on manual experience, though the application of intelligent sensors offers a solution to these resource inefficiencies. By embedding these specialized technologies into the garden environment, management can transition from subjective maintenance to data-driven precision. The traditional maintenance approaches are based on the regular checks and experience of estimations without dynamic control of the plant physiological condition and environmental situation, which leads to the obsolete maintenance programs, excessive or inadequate utilization of water and fertilizers, which impacts the health of crops and quality of ecological landscapes. As the complexity of the garden ecosystems grows, the design of a technical system capable of delivering multi-dimensional information collaborative perception, data-driven decision-making and automatic control has emerged as the major requirement of the computerized and smart design of gardens [1,2]. With the sensing, control and data fusion, real time monitoring of the status of the plant growth, scientific optimization in maintenance parameters could be realized, which is significant in value in terms of saving resources in maintenance, enhancing ecological quality and aiding in the development of smart gardens.

As the Internet of Things (IoT) technology grew in maturity, numerous ideas have been proposed to monitor the environment within gardens using the Wireless Sensor Networks (WSNs). Digital modeling of the plant physiological response mechanisms and data-driven intelligent control structures are the primary topic of international research, including the use of sensor networks with cloud computing to obtain large-scale ecological monitoring. Domestic research on the other hand leans more toward the regional gardens and facility agriculture with the focus of the economic efficiency of low power node deployment and data acquisition. The existing studies are still deficient in terms of data fusion accuracy, cooperation of multi-source sensors, and adaptive maintenance choice, particularly they lack a systematic mechanism of modeling dynamic coupling between the physiological attributes of the plant and the maintenance parameters. The question of finding accurate maintenance decisions on the basis of multi-dimensional environmental data has become one of the major bottlenecks on implementing IoT technology to manage gardens.

This research integrates IoT sensors into an information-based management system to build a technology platform for real-time garden plant monitoring and accurate nurturing. By leveraging the durability and sensitivity of these specialized materials, the platform satisfies the requirements for high-precision environmental data collection and long-term technical stability. The system incorporates the technologies of environmental perception and data analysis and gathers the main parameters of soil moisture, temperature, light intensity, air humidity and carbon dioxide concentration using multi-source sensors. A wireless sensor network is used to transmit real-time data and process it centrally. The features are identified with the help of data fusion algorithms and the state of the multi-dimensional information is determined. An accurate maintenance decision model can be built by integrating the fuzzy control and machine learning to obtain automated irrigation, fertilization and light [3,4]. In the Suzhou, Jiangsu experimental area, verification demonstrated very good results in the monitoring accuracy and control responsiveness which provided a theoretical framework and technical verification direction of the implementation of an intelligent garden maintenance system.

II. THEORETICAL FOUNDATION AND OVERALL SYSTEM ARCHITECTURE

The IoT system realizes the interconnection of the physical world and information space through a multilayered structure. Its core lies in collecting environmental and biological data through sensing technology and realizing intelligent decision-making through network communication and data processing models. Wireless Sensor Network (WSN) is a key supporting technology of IoT. It consists of a large number of low-power sensor nodes and has the characteristics of distributed deployment, self-organized communication and multihop transmission. The network structure usually includes a sensor node layer, a aggregation node layer and a central server layer. The nodes achieve stable data transmission through wireless protocols (such as ZigBee, LoRa, etc.). Theoretically, the performance of WSN depends on the energy consumption balance of nodes, data transmission delay and network robustness. In the garden environment, it is necessary to take into account the problems of signal attenuation, shading and weather disturbance. Through multi-node collaborative networking and adaptive data routing algorithm, high-time acquisition of environmental status and low-power communication can be achieved, providing a reliable data foundation and communication guarantee for monitoring the growth status of garden plants [5,6].

The ecological environmental factors interaction determine the growth of garden plants. Influential parameters that determine the physiological activities of plants include soil moisture, temperature, humidity of air, intensity of light, and the amount of carbon dioxide in the air. The moisture content of the soil has a direct impact on the capacity of the root system to take in water and other nutrients, temperature and humidity on the rate of photosynthesis and transpiration. The light intensity and photoperiod is a major factor in the production of chlorophyll and energy as well as the level of carbon dioxide is a key element that restricts the rate of photosynthesis. Along with environmental parameters, plant developmental conditions may be manifested in the form of leaf area index, chlorophyll content, and canopy reflectance. With this combination of parameters, it is possible to develop a multidimensional characteristic model of plant physiological state to determine the health and growth potential of plants. The important attributes are isolated in the process of data processing through Principal Component Analysis (PCA) and fuzzy clustering algorithms to feed the intelligent decision-making unit of the system, and with the help of this unit, dynamically map monitoring data to growth information.

The system architecture as a whole is built on a functional layered system of perception layer, transmission layer and application layer. The perception layer has various kinds of sensor nodes, embedded gain modules, and preliminary data processing units, which transform environmental and physiological parameters to digital signals; the transmission layer fulfills data aggregation, compression and transmission of data via wireless sensor networks and edge computing gateway, and provides a low latency communication framework that guarantees real time performance; the application layer combines data fusion, intelligent discrimination and decision control units, and realizes the presentation of monitoring results and control command feedback through databases and visualization systems. The system is based on the principles of the two-way closed-loop system, and the control signals of the application layer are fed back to the execution end via the transmission layer to achieve dynamic adjustment and adaptive maintenance [7,8]. This three-layer architecture implements a systematic process of data acquisition, transmission, decision-making, and execution through the integrated co-optimization of hardware and software.

III. MONITORING SYSTEM DESIGN AND DATA FUSION MODEL

A. DEPLOYMENT OF MULTI-SOURCE SENSOR NODES AND SENSOR DATA ACQUISITION

The sensor nodes of the monitoring system are distributed in a grid format depending on the plant community density and the terrain distribution with the mean distance between nodes to be 8 to 10 metres so as to assure the coverage of the signal and representation of the data. Each node incorporates a soil moisture sensor, a capacitive temperature, a photodiode-type light sensor, an infrared gas analysis module, and a unit of air humidity detection and multi-channel synchronous sampling is provided by a microcontroller unit (MCU). To enhance stability of the data, timing correction is performed at the acquisition end with the help of time synchronization protocol and the sampling frequency is set to 1 Hz to be able to have the continuous response of data needed under the dynamic environmental conditions. Nodes contain local buffer modules, which are able to store data packets temporarily in case of restricted communication and report them in batches after network recovery. The received signals are digitized (ADC) into digital format and a set format of data frames containing node number, timestamp and checksum are encapsulated. These frames are sent to the gateway device through a low-power communication device (e.g. ZigBee or LoRa) to gain a high-density low-power environmental data acquisition system.

B. DATA TRANSMISSION MECHANISM AND REAL-TIME MONITORING PLATFORM ARCHITECTURE

Layered architecture of the data transmission system is adopted, comprising of node layer, routing layer and the aggregate layer that facilitates multi-hop communication and dynamic data forwarding. Every node is automatically choosing a forwarding path according to the Received Signal Strength Indicator (RSSI) to prevent network congestion and unbalanced power distribution. Aggregation nodes will be installed at the high signal coverage locations in the monitoring area and handle the integration of the data and send it to the edge gateway. The edge gateway also interacts with the main server by the MQTT (Message Queuing Telemetry Transport) protocol and provides the safety of data transfer with the help of a lightweight encryption algorithm. The real-time monitoring platform assumes the B/S (Browser/Server) architecture, whereby the time-series database InfluxDB is employed as the high-frequency storage and indexing of data, the front-end is based on the WebSocket technology to provide data updates on a milliseconds basis, and the back-end is implemented by the Python asynchronous framework to allow the operation of multiple processes. The monitoring interface is able to dynamically show environmental parameters curves, spatial thermal distribution, and plant status alarm, and attain in-stream flow between acquisition of data and visualization.

C. DATA FUSION ALGORITHMS AND FEATURE EXTRACTION METHODS

Once multi-source sensor input is sent to the data fusion module, the noise suppression and outlier removal operation are done, however, minimizing signal variation using moving average and Kalman filtering. Subsequently, a multi-dimensional feature space construction algorithm transforms the parameters of the environment to a plant growth state feature matrix. To attain multi-parameter collaborative model, the fusion processing uses weighted recursive algorithm with weights adjusted adaptively as sensor accuracy and correlation coefficients vary to ensure that the fusion processing produces a reproducible and accurate result. During the feature extraction phase, Principal Component Analysis (PCA) is employed to decrease the dimensionality and obtain important features that denote the water state of the plant, the utilization of light energy, and gas exchange efficiency. The anomaly detection part is based on Isolation Forest algorithm to detect sudden changes which give early warnings of environmental stress or equipment failures. The results of the fusion are then converted with the help of fuzzy membership functions and fed into the decision model to obtain continuous discrimination and quantitative characterization of the plant status.

IV. INTELLIGENT DECISION-MAKING AND PRECISION MAINTENANCE CONTROL METHODS

A. FUZZY CONTROL AND MACHINE LEARNING ALGORITHMS

The decision making model of the system is based on a hybrid control structure of fuzzy logic and machine learning. Fuzzy control works on fuzzy inference of environmental variables into decision variables, whereas the machine learning module works on changing parameters in accordance to historical data. The fuzzy control subsystem establishes the input variables such as soil moisture, light intensity, air humidity, temperature, and carbon dioxide concentration, and the output variables such as irrigation threshold, fertilization ratio, and the supplemental light intensity. Membership functions are used to map continuous environmental variables to fuzzy linguistic values and the symmetric trigonometric functions are used to define low, medium and high levels. The rule base which is formed by the results of the regression analysis and the experience of the experts consists of 72 fuzzy rules of inference, which obtain fuzzy matching between nonlinear conditions and control commands through a Mamdani-type method of fuzzy inference. Defuzzification of the fuzzy output is by centroid method and converted into downstream algorithms control inputs. The machine learning part uses a multilayer perceptron (MLP) to supervised train the fuzzy output and historical control feedback using backpropagation to optimize the weight combination, making the system adapt itself to seasonal variations and variations in plant species.

B. INTELLIGENT DECISION-MAKING LOGIC FOR IRRIGATION AMOUNT, FERTILIZATION FREQUENCY AND LIGHT REGULATION

The intelligent decision-making logic generates irrigation, fertilization, and light regulation instructions by fusing fuzzy reasoning output with machine learning correction results. The system sets up a three-layer judgment mechanism: environmental state identification, maintenance demand calculation, and control intensity allocation. The environmental state identification module determines the growth stage and stress risk level based on the fused feature matrix, the maintenance demand module calculates the resource demand based on the soil water potential model and the photosynthetic efficiency model, and the control allocation module generates the regulation amount through weighted solution [9,10]. The decision logic structure is shown in Table 1.

TABLE 1. Mapping Relationship of Intelligent Maintenance Control Logic Parameters

Environmental input parameters	Fuzzy membership level	Control output variables	Adjustment range (%)
Soil moisture	Low/Medium/High	Irrigation start time	20–80
Light intensity	Weak/Suitable/Strong	Fill light power adjustment	15–60
Air humidity	Low/Medium/High	Spray cycle	10–40
Carbon dioxide concentration	Low/Medium/High	Ventilation execution frequency	5–30
Temperature	Low/Suitable/High	Shading net coverage ratio	10–50

This mapping table is used to dynamically constrain the output range, preventing energy consumption conflicts and resource over-compensation between different actions. Based on the light energy utilization curve and irrigation response delay model, the system adaptively fine-tunes the adjustment range to achieve steady-state growth control of plants under optimal photosynthetic and water balance.

C. AUTOMATED CONTROL EXECUTION MECHANISM AND FEEDBACK OPTIMIZATION STRATEGY

The execution system adopts a distributed control structure, with control commands sent from the host computer to the execution terminal via an edge controller. The irrigation unit consists of an array of solenoid valves and a pressure regulating pump, while the fertilization unit uses a proportional mixer and an electrically controlled valve for synchronous control. The light regulation end uses pulse width modulation (PWM) to drive an LED light source array to achieve variable power response. The control logic executes in a priority queue, adaptively adjusting the execution order based on real-time environmental conditions. The feedback mechanism detects environmental response and plant state changes after control execution through sensor nodes, compares these changes with a set threshold to calculate the deviation value ΔV, and feeds this back to the learning model to correct control parameters. The optimization algorithm employs an adaptive gain adjustment method to dynamically correct irrigation delay and fertilizer concentration responses. The system maintains a closed-loop structure to ensure the timeliness and accuracy of the control output under multi-variable conditions, achieving continuous self-adjustment under long-term conditions through iterative updates.

V. SYSTEM VALIDATION AND RESULT ANALYSIS

A. SYSTEM DEPLOYMENT AND EVALUATION PLAN FOR THE SUZHOU PILOT ZONE IN JIANGSU PROVINCE

The system is implemented in the Xiangcheng District Garden Demonstration Area of Suzhou City, which is located in Jiangsu Province and occupies an area of 3 hectares and hosts three vegetation types; trees, shrubs and lawns. The deployment of the monitoring nodes will be 45 in total with a monitoring radius of about 9 meters resulting in a coverage rate of about 95 percent. The nodes create a cellular communication topology using a LoRa network with the aggregation node being situated at a rather high altitude to reduce signal interference. The edge computing devices are placed near the control center, and linked to the management platform server through wired communications in order to implement simultaneous local preprocessing and data reporting. Depending on the type of plants, meteorological parameters, the operating parameters of the system are automatically changed and the frequency of a sample and the transmission interval are altered. Five indicators were chosen in performance evaluation, including monitoring error, data latency, system packet loss rate, energy consumption, and transmission stability. Average performance was calculated using a continuous 120-hour data acquisition cycle. Evaluation results are shown in Table 2.

TABLE 2. System Monitoring and Communication Performance Evaluation Indicators

Indicator Name	Test average	Maximum deviation in a single test	Performance stability coefficient
Monitoring error (%)	±2.3	4.7	0.93
Data latency (s)	1.45	2.1	0.96
Package swapping rate (%)	0.85	1.6	0.94
Node power consumption (mW)	72.4	84.3	0.91
Transmission stability index	0.95	—	—

Table 2 illustrates the communication and monitoring stability of the system under long-term operation. Monitoring errors are affected by the accuracy of the sensor module and environmental interference, while latency is mainly determined by network load and edge computing processing time. The stable values of each indicator indicate that the system has the capability to ensure continuous operation and data consistency.

B. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

After long-term operation, data related to plant growth and resource utilization were collected by comparing the traditional manual maintenance mode with the intelligent control mode of this system. Indicators included leaf area development rate, total water and fertilizer supply, energy utilization rate, and maintenance operation timeliness. The comparison period was set to 30 days. The results are shown in Figure 1.

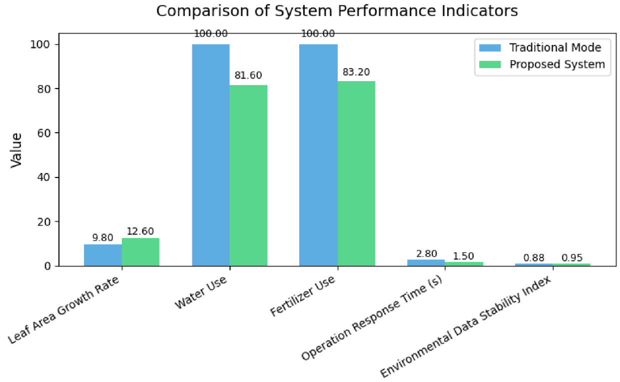

FIGURE 1. System operation optimization effect

The leaf area increase rate improved from 9.8% in the traditional model to 12.6%, indicating that the maintenance strategy better meets the physiological needs of plants in terms of light and water/fertilizer balance. The decreases in water resources and fertilizer application were 18.4% and 16.8% respectively, demonstrating the system's precise regulatory role in the closed-loop feedback control of soil moisture and nutrient concentration. The operation response time decreased from 2.8 seconds to 1.5 seconds, a 46.4% improvement in response speed, reflecting enhanced timeliness in the system's decision-making and execution chain. Through the rapid inference and low-latency data channels of edge computing nodes, control commands can reach the execution end within milliseconds, significantly reducing response lag. The system achieves triple optimization in energy saving, efficiency improvement, and steady-state control, validating the feasibility of multi-source sensor fusion and intelligent control in the field of garden maintenance.

VI. CONCLUSION

By integrating smart sensors within the IoT-based framework, this system achieves the organic fusion of environmental data and fabric-based moisture monitoring, demonstrating the stability of multi-source sensing and algorithmic optimization in managing both the garden ecosystem and its supporting infrastructure. The system is able to attain real-time responses of plants in the garden to multi-dimensional changes with regards to the environment, and have a self-learning and dynamic adjusting ability thereby enhancing the efficiency of the management and the sustainability of the ecological environment. The model is very robust in multivariate coupling conditions and is applicable to garden conditions of various vegetation structures and spatial scales. Nevertheless, the algorithm utilizes still experimental areas samples to learn parameters, and the generalization of the model is restricted by geographical and climatic dissimilarities. Future extensions of the training framework will incorporate multi-climate cross-regional datasets and integrated biosensors to enable a deep learning-driven visual monitoring system that maximizes the accuracy of plant physiological recognition and its interaction with high-performance fabrics.

AUTHOR CONTRIBUTIONS

Qishan Huang designed, collected and analyzed the data, and drafted the manuscript. Qishan Huang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qishan Huang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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