An Intelligent Health Monitoring System for Buildings Based on IoT Technology

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Abstract. This paper presents the design and development of an intelligent health monitoring system for buildings, utilizing IoT (Internet of Things) technology. In addressing a prevailing issue in current building stress monitoring methods, which often overlooks point cloud data preprocessing, we propose a method that focuses on monitoring vertical stress points in concrete structures and aligning the collected data with finite element analysis models. Subsequently, harnessing the potential of IoT technology, we design a Zigbee-based scheme for collecting environmental data within the building. This scheme incorporates a diverse array of sensors and encompasses the construction of a comprehensive software and hardware system alongside a monitoring platform. The resulting system is adept at real-time monitoring and data collection across various facets of the building, ensuring alignment with actual conditions. It demonstrates significant practical value, offering user-friendly operation, robust stability, and excellent performance in the realm of building monitoring.

Keywords: IoT Technology; Health Monitoring; Civil Engineering Structures; Point Cloud Registration; Sensors.

1. Introduction

Civil engineering structures undergo various forms of damage and deterioration over time due to environmental loads such as earthquakes, wind, waves, flows, temperature variations, as well as durability-related issues like fatigue, corrosion effects, and material aging, in addition to human-induced factors [1]. Structural damage can manifest as a decline in the inherent strength and stiffness properties of the structure or even encompass issues affecting the overall structure, including boundary conditions and connections, all of which result in diminished structural performance. Such structural damage can be categorized as sudden or cumulative. Structural health monitoring (SHM) emerged in the late 20th century as a prominent field in civil engineering. It found early and rapid application in bridge monitoring, gaining wide acceptance and development in this domain. For monitoring the early-stage compressive strength of concrete, IoT-based sensors are used to detect the temperature inside the concrete mix. This temperature is correlated with the heat of hydration and concrete age, which can be used with the maturity index method [2] endorsed by the American society for testing and materials and adopted by Carino for estimating the early-stage compressive strength of concrete. This method is used for different grades and mixes used in large concrete placements , sprayed concrete , polymer concrete , curing at variable temperatures , and improving the estimation of compressive strength in the late stages of curing . Many researchers have monitored the early-stage compressive strength of fresh concrete in laboratory samples , and some studies have monitored the early-stage compressive strength of concrete used in buildings. Zuo et al. [3] implemented an IoT-based remote real-time monitoring system on an under-construction, 250-m super high-rise RC building and concluded that this system can be applied remotely in real time with high accuracy. Inspired by the success of temperature-based sensors in the estimation of the compressive strength of concrete and in calibration through laboratory testing , commercial pocket-size, miniature Wi-Fi-enabled waterproof devices have been developed that are already used in industrial applications . These devices can be easily embedded in various structural members, such as beams, columns, and slabs. Perry et al. [4] employed a network of 11 thermocouple sensors to determine the strength of an concrete foundation by using the maturity method. In addition to the maturity index, which is a function of the temperature and time, smart aggregates embedded with piezoceramic material are used for determining the compressive strength by adopting wireless sensors. Petrakis et al. [5] proposed an SHM system for predicting the damage in concrete and brick specimens on the basis of Lamb wave amplitudes. Ultrasonic pulse velocities from both the aforementioned two types of specimens were compared with benchmark values to obtain an estimate of the damage inside laboratory specimens. Tareen et al. [6] performed a comparative study on the performance of smart temperature sensors and piezoelectric sensors . Yang et al. [7] conducted IoT-based monitoring of the concrete temperature and relative humidity when implementing automated concrete curing equipment . They selected a threshold value of 80% for relative humidity and >45°C for temperature to add a fogging spray to concrete. John et al. [8] adopted an IoT system to measure atmospheric temperature, concrete internal temperature and relative humidity for concrete specimens to determine the critical point for the initiation of plastic shrinkage cracks in hot weather conditions.

This paper focuses on large-scale civil engineering structures with substantial spans and presents an algorithm for preprocessing building point cloud data and monitoring vertical stress. Additionally, the collected data from critical structural locations, including stress and deformation, are analyzed to ensure structural safety, providing essential information for subsequent structural health monitoring and safety assessments. Furthermore, temperature sensors placed at key locations provide information related to temperature-dependent disasters such as fires, contributing to the development of an intelligent building health monitoring system.

2. Point Cloud Registration and Finite Element Analysis

In order to facilitate the monitoring of vertical stress points at critical locations within buildings, it is necessary to pre-capture relevant point cloud data pertaining to the vertical stress in building concrete [9]. However, conventional data acquisition methods do not guarantee that all point cloud data are in the same coordinate system, leading to difficulties in proper alignment and significant errors when attempting to merge the data. To address these issues, a siteless approach is adopted during point cloud data collection. Nevertheless, it is essential to ensure that there are three or more overlapping areas between two sites to facilitate point cloud data alignment. Given that the environment surrounding the buildings often introduces noise and superfluous data into the collected building point cloud data, the elimination of redundant data and noise is necessary during practical applications. The Gaussian filtering method [10] is primarily employed for data smoothing, which involves using a Gaussian filter to eliminate high-frequency noise in the useful data region. This noise reduction method effectively preserves the original data morphology.

Let us assume that the feature matrices extracted from the building concrete are denoted as matrices A and B. Both matrices comprise coordinates of m three-dimensional feature points. Matrix A serves as the standard matrix for all coordinate matrices, while matrix B is considered the mobile coordinate matrix. Precise alignment of data can be achieved by transforming matrix B coordinates based on the standard matrix A coordinates. The expression for matrix B after transformation is given as:

$$D = B \times R_x \times R_y \times R_z \times R_\theta \quad [1]$$

Here, D represents the matrix after transformation, R_x denotes the rotation matrix about the x-axis, R_y represents the rotation matrix about the y-axis, R_z is the rotation matrix about the z-axis, and R_θ represents the translation matrix for data points. The expression for the rotation matrix R_x is as follows:

$$R_x = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos x & -\sin x & 0 \\ 0 & \sin x & \cos x & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad [2]$$

Where α represents the translation length in the x-axis direction, β represents the translation length in the y-axis direction, and χ represents the translation length in the z-axis direction.

Following the transformation, there will be some error between the transformed matrix and the standard matrix. To quantify the error in the transformed matrix and subsequently construct an error function for data alignment, an error matrix is defined as:

$$H = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1q} \\ c_{21} & c_{22} & \cdots & c_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ c_{p1} & c_{p2} & \cdots & c_{qp} \end{bmatrix} = D - A \quad [3]$$

Here, H represents the error matrix for data point alignment. Subsequently, an error function for data alignment is derived as:

$$f(x, y, z) = \sum_{p}^{j} \sqrt{c_{p1}^2 + c_{p2}^2 + \cdots + c_{qp}^2} \quad [4]$$

Where p denotes the number of common feature points in the point cloud data, and q represents the dimensionality of the point cloud data feature points.

By adjusting the rotation matrices based on the error function, precision in aligning all common feature points is ensured, maximizing the overlap of all feature points. This process enables effective point cloud data alignment and enhances the accuracy of stress point monitoring.In order to ensure the accuracy of vertical stress point monitoring in prefabricated concrete assembly-style buildings, it is imperative to construct finite element models for concrete structures [11]. These models provide detailed information on various forces acting on concrete in three-dimensional space at different time intervals.

Within the concrete solid module, the equations governing stress-strain under the unit coordinate system can be expressed as:

For the x-axis stress equation in the coordinate system:

$$g = \left[\frac{1}{8} \begin{pmatrix} g_1(1-e)(1-o)(1-i) + \\ g_2(1+e)(1-o)(1-i) + \\ g_3(1+e)(1+o)(1-i) + \\ g_4(1-e)(1+o)(1-i) + \\ g_5(1-e)(1-o)(1+i) + \\ g_6(1+e)(1-o)(1+i) + \\ g_7(1+e)(1+o)(1+i) + \\ g_8(1-e)(1+o)(1+i) \end{pmatrix} \right] \quad [5]$$

Subsequently, the strain within the prefabricated concrete is calculated based on the stressequations of the finite element model, and the formula for strain calculation is as follows:

$$\partial(t, t_0) = [\phi(t_0)/W(t_0)][1 + \eta(t, t_0)] + \sum_{i=1}^{v} \frac{\Delta\phi(t_0)}{W(t_0)}[1 + \eta(t, t_1)] + \partial_i(t, t_0) \quad [6]$$

Here, $\phi(t_0)$ represents the original stress at time t_0 for the vertical stress point, $W(t_0)$ represents the elastic modulus of concrete after time t_0, $\partial(t, t_0)$ represents the shrinkage strain of prefabricated concrete at time t, $\eta(t, t_0)$ represents the creep factor of prefabricated concrete at time t, and $\Delta\phi(t_0)$ represents the increment of stress at the stress point. The formula for calculating the original stress of prefabricated concrete is as follows:

$$\phi(t_0) = \frac{\partial(t_0,t_0) - \partial_i(t_0,t_0)}{1+\eta(t_0,t_0)} \times W(t_0) \quad [7]$$

Here, $\partial(t_0, t_0)$ represents the observed numerical value of stress change at the stress point.

3. Design of IOT System

The monitoring system described in this section is a cloud-based dynamic monitoring and early warning service system designed with a modular approach. It comprises subsystems such as sensor systems, data acquisition systems, database management systems, safety warning systems, and safety assessment systems [12]. To overcome the limitations of traditional environmental testing methods, which often involve manual data recording and the use of single-parameter instruments and handheld devices, this paper presents a data acquisition system based on Internet of Things (IoT) sensors, with technical specifications as shown in Table 1.

Table 1: Sensor Selection for IoT-Based Building Health Monitoring System

Sensor	Model	Monitor Content	Measurement Accuracy
Temperature and Humidity	DHT11	Environmental Temperature and Humidity	±3
Smoke	MQ-2	Smoke Concentration	±50ppm
Vibration	SW1801P	Vibration Detection	±5%
Moisture Content	VMS-3000	Concrete Moisture Content	±3%
Dual-Axis Tilt	SINDT02	Building Tilt Angle	±0.1%
String Vibration Crackmeter	JM-S	Building Cracks	±0.1mm

The upper-level system includes both a PC-based LabVIEW upper-level system and an Android app. The Android app is typically used in situations with lower data acquisition density and shorter sampling periods. It provides real-time data display and audible alarms. By using Wi-Fi network connectivity, it extends the monitoring range of the system and addresses the limitation of a single monitoring approach in traditional methods. The PC-based LabVIEW upper-level system is suitable for multi-node data acquisition and long-term environmental monitoring. It offers a user-friendly interface for real-time display of system data, data aggregation into curves, data storage in designated folders, parameter threshold setting for alarms, and basic data analysis capabilities. The overall system framework is illustrated in Figure 1.

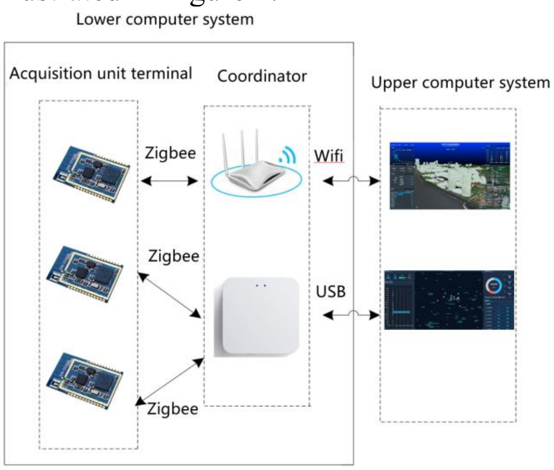


Figure 1: Overall framework of the Internet of Things system

The implementation and development of the system involve both upper-level and lower-level system development, including hardware and software components. The upper-level system consists of a coordinator and collection unit terminals, which perform different functions based on the Zigbee protocol standard. The coordinator and collection unit terminals can establish a stable Zigbee network and acquire various environmental quality data from the underlying sensors. Users of the system can obtain real-time environmental data through the human-machine interface. To ensure data accuracy, the system incorporates threshold settings to monitor the data range continuously. It also has automatic data storage capabilities to enhance monitoring efficiency. Considering variations in monitoring scenarios, the system is designed with both PC-based and Android-based monitoring app components to fulfill data display, storage, warning, and basic data analysis requirements. The lower-level system development utilizes virtual instrument software, with the PC-based upper-level system developed using LabVIEW program blocks and interface development to achieve the intended functionality. The Android-based upper-level system, or mobile app, includes interface design and backend programming.

Based on the hardware design requirements of the environmental data acquisition system and practical considerations, the lower-level system can be divided into two parts: the Zigbee minimum system and the function extension baseboard. These two parts are connected physically through interface circuits to fully utilize the I/O port resources of the CC2530 chip. In the lower-level system, the Zigbee minimum system plays a crucial role. It is responsible for data packaging and forwarding, Zigbee network establishment, Zigbee node network searching, and joining the network, among other tasks. The Zigbee minimum system includes the peripheral circuits of the main control chip, RF radio circuit, crystal oscillator circuit, and port configuration circuit. The function extension board includes the serial communication module, sensor module, power supply module, and other auxiliary modules. For example, in the coordinator case, the specific hardware diagram of the upper-level system is shown in Figure 2.

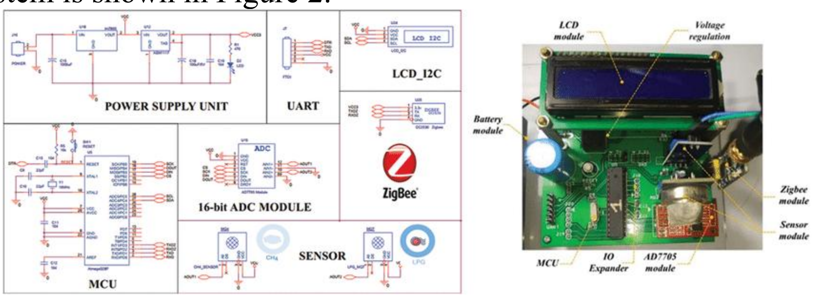


Figure 2: Hardware Diagram of the Lower-Level System

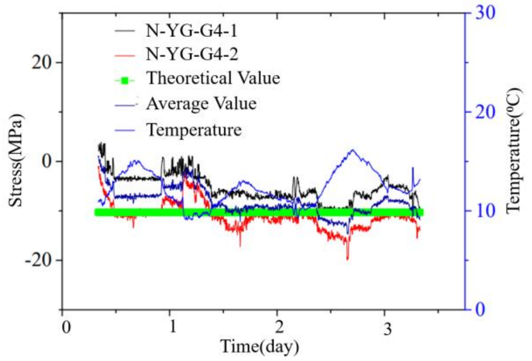
4. Experiments

Firstly, the accuracy of the proposed point cloud registration method in this paper is demonstrated. Real-time building health monitoring data is uploaded to the OneNET cloud platform via the WiFi module, and users can view current safety indicators on their mobile devices in real-time. The accuracy of point cloud data registration directly affects the accuracy of stress monitoring at force points, which in turn influences the overall monitoring precision. To eliminate randomness, 15 sets of vertical force points from different locations within a concrete structure were randomly selected for point cloud data registration.

Next, the effectiveness of the building health monitoring platform proposed in this paper is verified. The user interface of the building health monitoring platform is shown as Figure 3:

Figure 3. Building Health Monitoring Platform Interface

The health monitoring of a certain exhibition hall's truss unloading phase data is performed. As shown in Figure 4, on the unloading day, at the first and third unloading stages, there was a stepwise increase in compressive stress at measurement points 1 (B-YG-C4-1) and 2 (B-YG-C4-2), with a total variation range of -10 to 5 MPa. The temperature, on the other hand, exhibited an upward trend over time, with a decrease in temperature observed after 17:00, within a range of 15 to 24°C. Based on the analysis of monitoring data, a corresponding relationship between stress and temperature is depicted in Figure 5. It can be observed that stress and temperature exhibit a linear negative correlation with a high linear correlation coefficient (R= -0.9), indicating a strong correlation. This demonstrates the effectiveness of the monitoring system for building health.



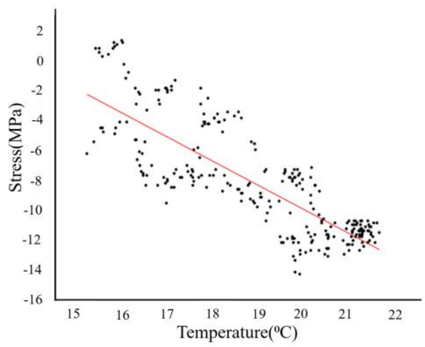


Figure 4: Correlation between Stress and Temperature Figure 5: Graphical Representation of Building Health Monitoring Results

These results confirm the effectiveness and reliability of the proposed building health monitoring platform in tracking stress variations and temperature changes during the unloading phase of the truss structure in the exhibition hall.

5. Conclusion

This paper has presented the design and implementation of an Internet of Things (IoT)-based intelligent building health monitoring system, along with its network architecture and system framework. The system was equipped with various features including visualization displays and a mobile application (App), all of which were demonstrated through an intuitive user interface. The primary goal of this system is to enhance building safety by providing real-time health monitoring capabilities, which contribute to more precise structural health assessments. The integration of IoT technology into the field of building health monitoring has proven to be instrumental in advancing the capabilities of structural monitoring systems. By utilizing a network of sensors and data communication channels, the system can continuously gather environmental data, detect anomalies, and issue timely warnings when safety thresholds are breached. This proactive approach to building health monitoring ensures that potential issues are identified and addressed before they can escalate into critical situations. As demonstrated through experimental validation, the proposed system exhibits good performance in accurately tracking changes in stress and temperature during various structural conditions, such as the unloading phase of a truss structure. The system's ability to establish correlations between environmental parameters and structural responses is a crucial asset for early detection of potential safety concerns.

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