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Development of a Smart Monitoring System for Urban Small-Scale Underground Excavation and Slope Safety

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ABSTRACT: The frequency of small-scale underground excavation and road construction in urban areas has increased due to rapid urbanization and population growth. This rise has corresponded with a higher incidence of ground and slope failures, as well as structural accidents. Current monitoring practices for ground structures are predominantly manual, limiting the ability to detect early warning signs and contributing to delayed responses and accident risks. Moreover, existing monitoring systems often lack efficiency and cost-effectiveness. To overcome these limitations, there is a pressing need for real-time, autonomous, low-cost, and highly efficient monitoring solutions. This study presents a newly developed smart monitoring system designed to measure ground structure displacements in urban excavation and slope environments, aiming to enhance safety in ground construction. The system incorporates advanced IoT sensors and AI technologies to improve measurement accuracy. A dedicated control and monitoring web platform was also developed to support the technology. By integrating automated data acquisition and transmission capabilities, the system enables real-time monitoring and analysis. Field tests conducted at active excavation and slope sites demonstrated the system's performance and confirmed its reliability.

KEYWORDS: Smart monitoring system, measurement system, automatic IoT sensors, field test.

1 INTRODUCTION

Rapid urbanization and population growth in recent years have significantly increased construction activity in urban areas, raising critical concerns about ground stability. Small-scale excavation sites and steep-slope construction zones are particularly vulnerable, often receiving inadequate attention in terms of safety management. This neglect has led to a disproportionately high accident rate, and fatalities at small-scale construction sites are reported to be approximately 4.43 times higher than those at medium- and large-scale sites (Hwang et al., 2023).

Moreover, the combined effects of climate change and intense rainfall have exacerbated the instability of steep slopes, increasing the likelihood of ground collapses and landslides, which highlights the urgent need for real-time monitoring systems and proactive risk management strategies, and these challenges are even more pronounced at small-scale sites where limited manpower and constrained budgets hinder effective safety practices in both developing and developed countries (Dumrak et al., 2013; López et al., 2008), while temporary excavation retaining walls are often undervalued in terms of structural importance, leading to insufficient safety consideration and oversight (Bian & Huang, 2006).

A key limitation at such sites is the continued reliance on manual monitoring methods, which typically involve infrequent data collection and lack real-time responsiveness. As a result, early warning signs of structural failure often go undetected. Barriers to adopting automated monitoring technologies include high initial costs, insufficient workforce training, regulatory hurdles, and skepticism toward emerging technologies (Redmon et al., 2016). These issues are especially prevalent in privately funded construction projects, where safety oversight tends to be weaker.

Recent advances in the Internet of Things (IoT) and Artificial Intelligence (AI) have introduced new paradigms for structural and geotechnical monitoring (Mathur et al., 2022). IoT-based systems, particularly those utilizing MEMS (micro-electro-mechanical systems) sensors, offer high-precision, real-time measurements of displacement, vibration, and pressure, allowing for early detection of structural anomalies (Mei et al., 2019; Carri et al., 2021). Meanwhile, AI-based image analysis provides enhanced visual monitoring, enabling accurate risk identification through object recognition techniques (Redmon et al., 2016; Zheng et al., 2021).

In response to these challenges and opportunities, this study presents the design and development of a smart monitoring system tailored for urban small-scale excavation and steep-slope sites. The system integrates IoT-enabled sensors and AI-powered image analysis to provide real-time, automated displacement monitoring. It is supported by a web-based control platform that facilitates data acquisition, transmission, and analysis. The system's effectiveness and reliability were validated through field deployments at active construction sites.

2 DESIGN AND DEVELOPMENT OF THE SMART MEASUREMENT SYSTEM

2.1 *Development of smart data device and data logger*

Advancements in sensor and embedded system technologies have significantly enhanced the performance and accuracy of ICT-based measurement devices, and modern microcontroller units (MCUs) now offer low-power operation and high-speed data processing, enabling the real-time acquisition and analysis of high-resolution data, while technologies such as solar power, radio frequency (RF), long-range (LoRa) communication, Bluetooth, and IoT-based machine-to-machine (M2M) networks have mitigated the challenges associated with constrained installation environments. MEMS sensors offer the ability to measure multiple physical parameters simultaneously, including temperature, humidity, acceleration, and angular velocity, and the Inertial Measurement Unit (IMU), which combines accelerometers, gyroscopes, and magnetometers, enables precise tracking of structural motion and orientation, and in particular, accelerometers are effective for detecting mechanical vibrations and shocks, and they provide accurate angle measurements when the device remains stationary.

The smart monitoring system developed in this study includes both ground and slope-specific sensors, and the ground sensor integrates a 6-axis displacement sensor with temperature and humidity sensors, as well as a 9-axis IMU (comprising a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer) to capture accurate displacement data along the X, Y, and Z axes. GPS functionality is included for spatial positioning, while Bluetooth Low Energy (BLE) ensures real-time data transmission even in areas with limited connectivity, and the device is designed for energy efficiency, operating at less than 20 mA/h and powered by a compact solar panel to ensure reliable, continuous operation. The hardware is enclosed in a lightweight, miniaturized casing, and neodymium magnets and brackets are used to simplify installation and removal in field conditions. Figure 1 presents the hardware architecture, firmware, and circuit diagrams of the smart data logger, and Figure 2 displays the developed prototypes, including smart sensors for both steep slopes and small-scale excavation sites, along with the data logger unit.

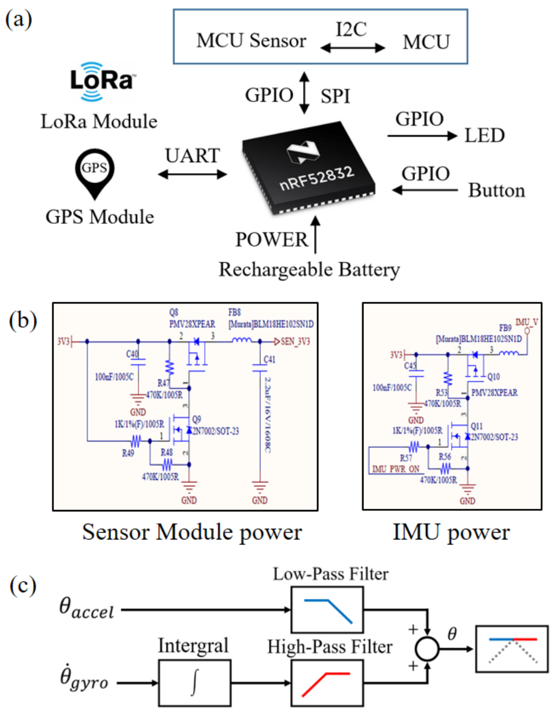

Figure 1. Designed hardware, F/W, and circuits for smart data loggers: (a) Circuit design, (b) Hardware design, and (c) Firmware design.

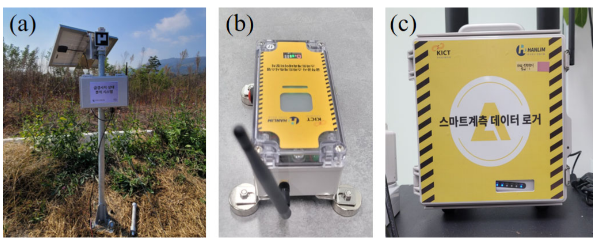

Figure 2. Smart data devices and data loggers: (a) smart data device for steep-slope construction work, (b) Smart data device for small-scale excavation work, and (c) Data logger.

2.2 *Architecture design of the smart measurement management system*

The architecture of the smart measurement and management system was developed to enable real-time safety monitoring and data-driven decision-making for small-scale excavation and steep-slope construction projects, and the system comprises LoRa- and LTE-based gateways, cloud servers, and a web-based real-time monitoring platform. To enhance measurement accuracy, the device firmware utilizes a complementary filter that fuses accelerometer and gyroscope signals, effectively reducing noise and producing stable displacement and angle data, and these processed data are then transmitted to the cloud server in real time via the designated gateway. The cloud server collects and manages key information from each sensor device, including displacement, GPS coordinates, battery status, and other operational data, and when abnormal values exceed predefined thresholds, the system automatically triggers alerts or warning notifications. The web-based monitoring platform features an intuitive dashboard interface that displays installation status, real-time alerts, time-series data analysis, and device-specific performance metrics, and it also supports 3D visualization and digital twin modeling based on collected measurements, enabling advanced structural stability assessments and risk prediction. The main technical specifications and performance parameters of the smart measurement device are summarized in Table 1.

Table 1. Performance of the smart measurement data device prototype.

Category	Applied content
Accuracy of measurement & reliability	3-axis sensor, ±0.1° accuracy, GPS, complementary filter
Data transmission	LoRa, >95% success rate, >1 km range
On-site applicability	Low-power, solar panel, lightweight, easy installation, AI video monitoring
Design features	Compact, portable, solar-powered

2.3 *Design of a state analysis system combining IoT sensors and AI cameras*

While physical sensors are effective for detecting external displacement in slopes and structures, they are limited in capturing behavioral patterns or subtle surface changes, and this limitation has led to a growing interest in video-based monitoring solutions. In this study, an AI-powered camera system was implemented to complement slope sensors by enabling visual analysis through object detection, and the system employs a YOLOX-based object detection algorithm, which builds upon the YOLO architecture by adopting an anchor-free and decoupled head structure, and YOLOX incorporates advanced data augmentation strategies to enhance robustness against variations in resolution and environmental conditions (Zheng et al., 2021). The AI camera used in the system supports Full HD resolution (1920×1080), automatic day/night mode switching, fog correction, and real-time video transmission via LTE and LoRa networks. Unlike traditional YOLO, which comprises 24 convolutional layers and two fully connected layers, YOLOX eliminates the fully connected layers and adopts a fully convolutional, anchor-free design with a decoupled head, which significantly improves detection speed and accuracy. Design considerations for the AI camera system are summarized in Table 2, covering object detection, model optimization, training enhancement, and support for varying environmental conditions.

Table 2. Design considerations for the AI camera algorithm

Category	Design considerations
YOLO-based object detection	Object detection and tracking using YOLOX or more advanced models
Detection accuracy improvement	Enhanced negative learning to minimize false positives; input size optimization per module
Model separation	Dedicated AI models for day and night, with multi-input algorithm support
Data augmentation	Address data imbalance; auto-filtering based on image quality (contrast, brightness)
Training value optimization	Auto-tuning of input parameters (input size, HSV values, etc.) for each image

2.4 *Real-time monitoring web system implementation and gateway communication design*

A web-based control system, integrated with a LoRa gateway communication framework, was developed to enable efficient processing, analysis, and visualization of sensor data in real time, and this system supports stable data transmission, continuous monitoring, automatic alert generation, and time-series data analysis through an interactive web interface. The overall system workflow is depicted in Figure 3. The architecture includes a LoRa master gateway that receives serial data from multiple smart sensor devices, and this data is locally processed and stored at the gateway before being transmitted to the control server via HTTP. The control server manages the incoming data by storing it in a structured database and performing real-time analysis based on key parameters such as displacement, GPS location, and battery status. The system's backend infrastructure incorporates data processing pipelines, GPS data collection, web API integration, server configuration, and deployment within an Nginx-based web environment, ensuring efficient communication and robust performance.

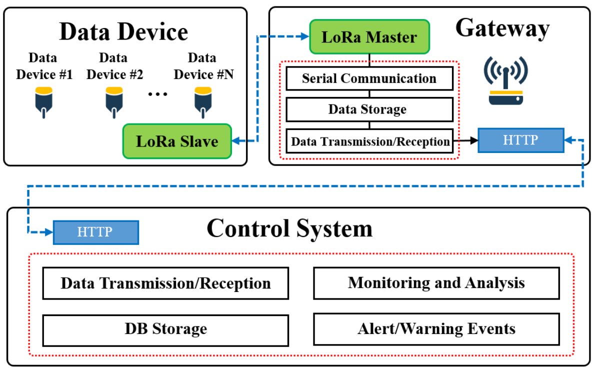

Figure 3. Transmission and reception data processing

The gateway layer is designed to reliably process data collected at the site, and it receives serial data from multiple LoRa-based measurement devices installed on site, performs basic integrity checks such as ACK responses and checksum verification, and then forwards the validated data to the control server over HTTP. The control server stores the received data in a structured database and, using key sensor information required for on-site safety assessment such as displacement, GPS location, and battery status, provides real-time monitoring, alert generation, and web-based visualization to enable early detection of abnormal conditions. To support this workflow, the web platform integrates data I/O modules, GPS data acquisition, Web API services, server configuration, and an Nginx-based deployment environment, so that the on-site early warning system can operate stably and be scaled as needed.

3 PERFORMANCE EVALUATION AND VERIFICATION OF THE SMART MONITORING SYSTEM

3.1 *Overview of on-site performance evaluation*

Following an initial laboratory evaluation to verify data acquisition and transmission stability, a field performance assessment was conducted at two real-world locations: a small-scale excavation site and a steep slope, and the objective was to comprehensively validate the smart monitoring system's functionality and reliability under actual site conditions. The excavation site selected for testing was a pipeline construction project, chosen to assess the applicability of the monitoring system to temporary retaining structures. A demonstration test was carried out on a retaining wall structure measuring 8.3 m × 8.3 m with a depth of 13.6 m. A total of ten smart measurement devices and two data loggers were deployed to evaluate displacement monitoring capability and the performance of data transmission and reception. Figure 4 shows the layout of the retaining structure and the configuration of the installed monitoring equipment.

Figure 4. Field deployment of the IoT-based monitoring system at a small-scale excavation site: (a) smart sensor device installed on the earth-retaining wall, (b) overview of the excavation site with installed strut system, and (c) smart monitoring system with solar panel mounted on the retaining structure.

To evaluate the performance of the integrated IoT and AI-based monitoring system under steep-slope conditions, a 5 m-high slope with a 1:0.56(V:H) gradient was selected as the testbed. Smart sensor devices were installed, as shown in Figure 5.

Figure 5. Field application of smart monitoring system at a steep slope Site.

To evaluate the device's measurement performance, artificial displacement was induced using three-directional tension wires, and simultaneously, AI-based image analysis results were compared with sensor measurements to assess accuracy. A lightweight, low-power glyph recognition algorithm based on AForge.NET was employed for image processing, and to enhance computational efficiency, only the target region was extracted from the original 8 MP images. As shown in Figure 6, preprocessing included repeated morphological operations such as dilation and erosion to enhance edge features.

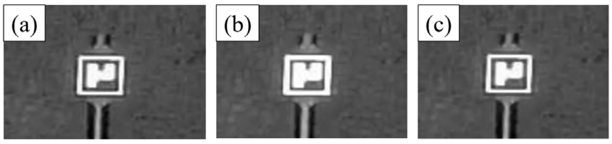

Figure 6. Preprocessing steps for the target image: (a) grayscale, (b) dilation, and (c) erosion.

Figure 7 shows the detection results based on YOLOX, demonstrating how the AI algorithm effectively recognized and tracked target objects.

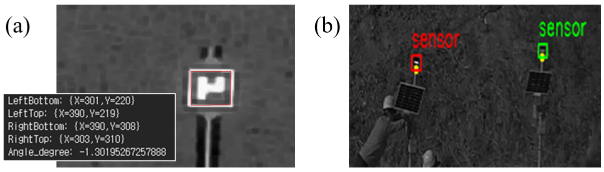

Figure 7. YOLOX-based detection results: (a) target object with pose estimation and (b) sensor detection.

3.2 *Performance evaluation and verification results*

Field demonstrations confirmed the stable performance of the smart monitoring system at both the excavation and steep slope sites. At the excavation site, measurements from the devices installed on the temporary retaining wall closely mirrored those from conventional inclinometers, showing minimal angular variation with a maximum angular displacement of 0.1°. At the steep slope site, AI-based image analysis estimated displacement and displacement velocity by tracking changes in the LED target images, and these results were compared against predefined GRID parameters and reference measurements. As illustrated in Figure 8, the AI-detected angle (5.2°) closely aligned with the actual reading from a digital inclinometer, validating the algorithm's accuracy. Overall performance, summarized in Table 3, indicated an average angular error of 0.54° and an average displacement error of 24.2 mm when benchmarked against actual measurements and IoT sensor data. Additionally, data transmission reliability was demonstrated with only four missed receptions out of 750 transmissions, yielding a data acquisition rate of 99.47%, surpassing the target threshold of 95%.

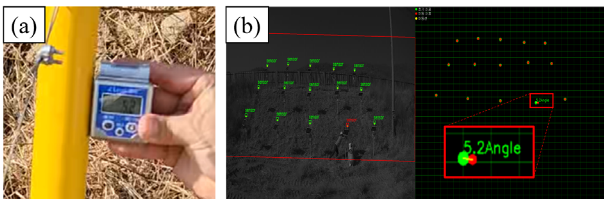

Figure 8. Detection result image based on YOLOX: (a) measured value of the digital inclinometer: 5.2°, (b) AI-based image analysis: 5.2°.

Table 3. Summary of field Performance evaluation results of the smart monitoring system

Category	Design considerations
Smart data device	Comparable to inclinometer readings Max angular displacement: 0.1° angle error: 0.54° displacement error: 24.2 mm
Data logger	Stable 1:N transmission 4 missed out of 750 receptions acquisition rate: 99.47% (target ≥95%)

4 CONCLUSION

This study evaluated the performance of a newly developed smart monitoring system integrating IoT sensors and AI-based image analysis through field applications at a small-scale excavation site and a steep slope. The system was designed to enable high-precision displacement monitoring and real-time structural risk assessment in challenging construction environments.

Field results demonstrated strong performance and reliability. The system achieved a data acquisition success rate of 99.47% and a maximum angular displacement error of just 0.1°. The AI-based image analysis showed high consistency with both sensor data and actual field measurements. The YOLOX-based AI camera reliably detected LED targets under both daytime and nighttime conditions, achieving an average angular error of 0.54° and a displacement error of 24.2 mm.

These findings confirm the effectiveness of IoT- and AI-enabled monitoring systems for accident prevention and safety management in small-scale excavation and steep-slope construction projects. Future deployment of this system across a wider range of construction and slope environments is expected to significantly enhance site safety and support proactive risk management in urban infrastructure development.

5 ACKNOWLEDGEMENTS

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