Research on Key Technologies and Safety Warning of Deep Excavation Support Structures Based on Multi Source Sensing and Real Time Data Fusion

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ABSTRACT Deep excavation support structures exhibit nonlinear and spatiotemporally coupled deformation under complex geological conditions and construction disturbances, making single-sensor monitoring insufficient for real-time safety warning. This study proposes a multi-source sensing and real-time data fusion method for safety early warning of deep foundation pit support structures. A heterogeneous sensor network composed of strain gauges, inclinometers, axial force gauges, and hydrostatic levels is deployed to monitor pile bending moment, horizontal displacement, support axial force, and surface settlement. Sensor streams with different sampling rates are temporally aligned by cubic spline interpolation and spatially mapped onto a unified support-pile profile. Outliers are removed using the Pauta criterion, and adaptive inverse-variance weighting is combined with Kalman filtering to obtain robust fused feature sequences. An improved grey relational analysis model with exponential time weighting and dynamic thresholds is then used to identify typical failure modes and issue three-level warnings. Field experiments using 30 days of monitoring data show that the method achieves 98.3% effective data retention, 20.3 dB signal-to-noise ratio, RMSE of 0.34 mm, warning response time of 4.2 s, and false alarm rate of 8.6%. The method improves structural sensing reliability and real-time safety warning capability.

INDEX TERMS deep excavation, multi-source sensing, kalman filtering, grey relational analysis, early warning

I. INTRODUCTION

DEEP foundation pit engineering is an important link in the development of urban underground space. The stress and deformation characteristics of the support structure during the excavation and use process of the foundation pit engineering will directly affect the safety of the surrounding environment and the construction period. However, foundation pit engineering has the characteristics of complex geological conditions, frequent construction disturbances, and drastic load changes. There is multidimensional, nonlinear, and spatiotemporally coupled deformation of the support structure [1,2]. Traditional monitoring methods are often based on single type sensors (that is, only the axial force of the support is monitored or only the strain of the pile body is monitored), the data of each measuring point are analyzed separately, which makes it difficult to reflect multidimensional characteristics. In addition, early warning values usually take fixed thresholds, and the data correlation and dynamic evolution relationship between different sensors are not considered. Therefore, it is easy to be affected by the environmental noise and local anomalies, causing frequent false alarms and missed alarms. In addition, data acquisition and processing are usually offline, resulting in delayed early warning response and unable to meet the real-time safety management requirements of engineering projects. In order to solve the safety monitoring and early warning problems of the support structure of the deep foundation pit engineering, scholars at home and abroad have carried out in-depth research on these problems. For example, Ren et al. carried out deformation monitoring and remote analysis research on the ultra-deep underground space excavation, and verified the effectiveness of various monitoring methods in complex working conditions [3]; Sun et al. analyzed the force evolution process of foundation pit excavation by integrating support axial force servo technology, numerical simulation and on-site monitoring [4]; in addition, Zhang Weicong studied the application of intelligent sensors in foundation pit support monitoring, and provided technical basis for improving monitoring automation and real-time performance [5]. However, the existing research is mostly based on single type of sensor data and specific working conditions, and the spatiotemporal correlation and complementarity between multi-source heterogeneous sensors are not fully utilized. Moreover, the early warning model usually takes a fixed data stream, and it is difficult to dynamically update the dynamic data stream, which makes it hard to balance real-time performance and accuracy. To solve the above problems, some scholars have tried to introduce multi-source data fusion technology into the field of foundation pit monitoring. For example, Shao proposed a distributed consistent Kalman filter method for asynchronous multi-frequency sensor networks, which effectively solved the problem of asynchronous time of multi-source data [6]; Mumuni and Mumuni improved the covariance adaptive strategy to achieve dynamic adjustment of noise and accuracy improvement in the sensor data fusion process [7]. However, simple weighted fusion cannot adaptively adjust the weights based on the real-time signal-to-noise ratio of each sensor, while single filtering methods struggle to handle outliers and data loss. Furthermore, how to efficiently integrate the fused features with the early warning model remains a lack of systematic research. Therefore, this paper proposes a real-time data fusion strategy based on adaptive weighted fusion and Kalman filtering, and on this basis, constructs a three-level early warning model with improved grey relational analysis and dynamic threshold updates. This paper aims to establish a safety early warning method for deep foundation pit support structures based on multi-source sensing and real-time data fusion. First, a multi-source heterogeneous sensor network encompassing strain gauges, inclinometers, axial force gauges, and hydrostatic levels is constructed. Second, adaptive weighted fusion and Kalman filtering are used to perform spatiotemporal alignment, anomaly removal, and dynamic correction on the data. Finally, combined with the fused dynamic data stream, an improved grey relational analysis and dynamic threshold three-level early warning model is established.

II. DEPLOYMENT AND DATA ACQUISITION OF MULTI-SOURCE HETEROGENEOUS SENSOR NETWORK

In order to realize overall perception of multi-dimensional stress and deformation field of deep foundation pit support structure, four kinds of heterogeneous sensors are arranged at appropriate sections of the foundation pit for bending moment, horizontal displacement of the support piles and axial force of the support piles and surrounding surface settlement monitoring. The arrangement scheme of four kinds of sensors is shown in following:

(1) Strain Gauges: Reinforcing bar strain gauges are symmetrically arranged on the longitudinal main reinforcing bars of the support piles, with one measuring point every 3 m along the depth direction of the pile, for a total of 8 measuring points. The sampling frequency is 1 Hz, used to continuously collect the distribution and trend of the bending moment of the pile.

(2) Inclinometer: Inclinometer tubes are pre-embedded in the foundation pit retaining structure. A movable inclinometer is used, with one measuring point every 2 m and a measuring point spacing of 0.5 m, covering the entire pile length range. The sampling frequency is 0.5 Hz, to obtain the deep horizontal displacement curve of the support structure.

(3) Axial Force Gauges: Vibrating wire axial force gauges are installed at both ends and mid-span of each reinforced concrete support, totaling 12 measuring points. The sampling frequency is 0.2 Hz. Real-time monitoring of axial force changes in the supports is used to determine if the stress on the support system exceeds limits.

(4) Static Leveling Instruments: Static leveling monitoring points are arranged along the ground surface around the foundation pit and near important buildings, with a spacing of 15 m, totaling 16 measuring points. The sampling frequency is 0.1 Hz, automatically collecting differential settlement data. All sensors are synchronously triggered for data acquisition via a field data acquisition unit (DTU). Data is uploaded to a cloud server in real-time via a 4G network. The different sampling frequencies and data formats of each sensor constitute a typical multi-source heterogeneous sensor network. The raw data includes fields such as timestamp, sensor number, physical quantity value, and equipment status, providing basic input for subsequent data fusion and early warning analysis. See Table 1 for detailed sensor deployment parameters.

TABLE 1. Deployment Parameters of Multi-Source Heterogeneous Sensors

Sensor Type	Monitoring Parameter	Number of Points	Installation Location	Sampling Frequency (Hz)	Range	Accuracy
Rebar strain gauge	Pile bending moment	8	Main reinforcement of retaining pile	1	$\pm 1500\mu\epsilon$	$1\mu\epsilon$
Portable inclinometer	Deep horizontal displacement	12	Inclinometer tube	0.5	$\pm 30^\circ$	0.01 mm/0.5 m
Vibrating wire load cell	Strut axial force	12	Both ends and midspan of strut	0.2	0–10000 kN	1%F.S.
Hydrostatic level	Ground surface settlement	16	Surrounding ground of excavation	0.1	± 50 mm	0.1 mm

III. SPATIOTEMPORAL ALIGNMENT AND ANOMALY REMOVAL OF SENSOR DATA

Due to differences in sampling frequencies (0.1 Hz to 1 Hz) and start-up times among different sensors, the raw data exhibits a non-uniform distribution along the time axis. To meet the data synchronization requirements of subsequent fusion calculations, temporal alignment is performed first. Using 1 Hz as the unified target frequency, cubic spline interpolation is employed to resample the discrete measurement points of each sensor. For any sensor's measured value $x(t_i)$ at time t_i, a cubic spline function $S(t)$ is constructed that passes through all known points and is second-order continuously differentiable within the interpolation interval, thereby obtaining the estimated value $\hat{x}(t_j)$ at the target time t_j. During the interpolation process, only missing or lost data segments are filled in, while the original valid data points remain unchanged to avoid introducing additional errors.

In terms of space, since the strain gauge, inclinometer, axial force gauge and static level are installed in the pile body, support and ground surface with different locations, the spatial coordinates of each points of measurement are inconsistent. Therefore, this paper take the longitudinal profile of support pile as the reference benchmark and interpolate the support axial force and surface settlement data into the corresponding pile depth position, so as to realize the representation of multi-source data in space with the same spatial coordinates.

Data quality directly affects the fusion effect, and outlier detection and removal are required for the original sensor data. The Pauta criterion (3σ criterion) is adopted. For the continuous monitoring sequence of each sensor, its mean μ and standard deviation σ are calculated. If the measured value x_k at a certain moment satisfies $|x_k - \mu| > 3\sigma$, it is judged as an outlier and excluded from the effective dataset for subsequent processing. This criterion is suitable for cases with a large amount of data and an approximately normal distribution, and can effectively identify gross errors caused by sensor failure or strong external interference. After removing outliers, cubic spline interpolation is used again to fill in the missing positions to ensure the continuity and integrity of the data sequence and provide reliable input for subsequent adaptive weighted fusion and Kalman filtering.

IV. ADAPTIVE WEIGHTED FUSION AND KALMAN FILTER DYNAMIC CORRECTION

Multi-source sensor data after spatiotemporal alignment and anomaly removal still need further fusion to extract comprehensive feature indicators with high confidence. This paper adopts a two-step method: first, adaptive weighted fusion is achieved based on the inverse variance, and then dynamic smoothing and noise suppression are performed through Kalman filtering.

A. ADAPTIVE WEIGHTED FUSION

The measurement accuracy and reliability of different sensors at the same time vary, and fixed weights cannot adapt to changes in noise levels. Therefore, an adaptive weighted fusion strategy is adopted, which dynamically allocates weights according to the real-time variance of each sensor.

Let the measurement value of the i-th sensor at time t_k be $z_i(k)$, and its local variance $\sigma_i^2(k)$ be calculated through a sliding window (window length $L = 20$), as shown in formula (1):

$$\sigma_i^2(k) = \frac{1}{L-1} \sum_{j=k-L+1}^{k} (z_i(j) - \bar{z}_i(k))^2 \tag{1}$$

where $\bar{z}_i(k)$ is the mean within the window. The adaptive weight $w_i(k)$ is defined as (2):

$$w_i(k) = \frac{1/\sigma_i^2(k)}{\sum_{j=1}^{n} 1/\sigma_j^2(k)} \tag{2}$$

where $n = 4$ is the total number of sensors. If a sensor's data is NaN or its local variance is too large (greater than the threshold 10^4), its weight is reset to zero to avoid polluting the fusion result with inferior data. The final weighted fusion value $u(k)$ is (3):

$$u(k) = \sum_{i=1}^{n} w_i(k) \cdot z_i(k) \tag{3}$$

This strategy automatically makes the fusion result tend towards the sensor with higher accuracy, improving the robustness of the fusion sequence. Table 2 shows examples of real-time weight allocation for each sensor under different operating conditions.

B. KALMAN FILTER DYNAMIC CORRECTION

The sequence $u(k)$ after adaptive weighted fusion still contains some random noise and needs further smoothing. Discrete Kalman filtering is used for dynamic state estimation, treating the true characteristics of the support structure as a linear dynamic system.

The system state equation and observation equation are (4-5):

$$x(k) = A \cdot x(k-1) + w(k) \tag{4}$$

TABLE 2. Example of Adaptive Weighted Fusion Weights

Time (h)	Working Condition	Strain Gauge Weight	Inclinometer Weight	Axial Force Meter Weight	Static Level Weight
12.5	Normal construction	0.32	0.28	0.25	0.15
45.2	Local disturbance	0.45	0.30	0.18	0.07
82	Abnormal deformation	0.28	0.42	0.22	0.08

$$u(k) = H \cdot x(k) + v(k) \tag{5}$$

where $x(k)$ is the true feature value to be estimated, $A = 1$ (assuming the deformation is approximately constant over a short period of time), $H = 1$; $w(k)$ and $v(k)$ are the process noise and observation noise,

respectively, with their covariance set to $Q = 0.01$ and $R = 0.5$. This combined method utilizes the complementarity of multi-source data and suppresses high-frequency noise through dynamic filtering, significantly improving the smoothness and accuracy of the feature sequence.

V. IMPROVED GREY RELATIONAL ANALYSIS AND CONSTRUCTION OF A THREE-LEVEL EARLY WARNING MODEL

A. ESTABLISHMENT OF TYPICAL FAILURE MODE REFERENCE SEQUENCES

Based on common failure modes of deep foundation pit support structures (such as excessive pile bending moment, excessive lateral displacement, sudden increase in support axial force, and excessive surface settlement), combined with on-site geological conditions and design documents, four sets of typical failure mode reference sequences $X_0^{(m)} = \{x_0^{(m)}(1), x_0^{(m)}(2), \ldots, x_0^{(m)}(T)\}$ were established, where $m = 1, 2, 3, 4$ correspond to the above four failure modes respectively, and T is the length of the fusion sequence. The characteristic values of each reference sequence were set according to the Technical Standard for Monitoring of Building Excavation (GB 50497) and site-specific engineering experience. Specifically, the limits for the reference sequences were defined as: 35 mm for cumulative horizontal displacement, 3 mm/day for displacement rate, and 80% of the design value for support axial force. These values reflect the typical evolution trend before failure.

B. IMPROVED GREY RELATIONAL DEGREE CALCULATION

Let the current fusion characteristic sequence be $X_c = \{x_c(1), x_c(2), \ldots, x_c(T)\}$. Traditional grey relational degree uses the average of equally weighted correlation coefficients, which is difficult to highlight the importance of recent data. This paper introduces a time weight factor to construct an improved grey relational coefficient. First, calculate the correlation coefficients at each time step under the m-th failure mode, as shown in formula (6):

$$\xi_m(k) = \frac{\min_m \min_k \left|x_0^{(m)}(k) - x_c(k)\right| + \rho \cdot \max_m \max_k \left|x_0^{(m)}(k) - x_c(k)\right|}{\left|x_0^{(m)}(k) - x_c(k)\right| + \rho \cdot \max_m \max_k \left|x_0^{(m)}(k) - x_c(k)\right|} \tag{6}$$

where ρ is the resolution coefficient, and we take $\rho = 0.5$. Then, we introduce the exponential decay time weight $\lambda_k = e^{-\alpha(T-k)}$, where α is the decay factor. In this study, α is set to 0.05 based on a sensitivity analysis where values ranging from 0.01 to 0.1 were tested; $\alpha = 0.05$ provided the optimal balance between filtering historical noise and maintaining sensitivity to rapid deformation rate changes typical of foundation pit failure stages. This ensures that recent data are given higher weight while retaining sufficient historical context. The improved grey relational degree is (7):

$$\gamma_m = \frac{\sum_{k=1}^{T} \lambda_k \cdot \xi_m(k)}{\sum_{k=1}^{T} \lambda_k} \tag{7}$$

The maximum relational degree $\gamma_{\max} = \max_m \gamma_m$ is taken as the matching degree between the current working condition and the most similar failure mode.

C. DYNAMIC THRESHOLD AND THREE-LEVEL EARLY WARNING OUTPUT

Traditional fixed thresholds are difficult to adapt to changes in the construction stage and environmental interference. This paper adopts a dynamic update strategy. The dynamic threshold is updated every 30 minutes. This interval was selected to match the typical stability period of support stress between construction cycles while allowing for the identification of sudden creep. The thresholds are calculated based on the 95th percentile of the fused data stream within the preceding 4-hour sliding window, ensuring the limits adapt to the current construction stage (e.g., active excavation vs. dormant periods) rather than remaining static. When the relational degree exceeds the corresponding threshold, the system automatically outputs the corresponding early warning level and pushes it to the on-site monitoring platform. This model dynamically matches multi-source fusion features with failure modes, realizing a closed-loop linkage from data perception to risk judgment.

VI. INTEGRATION OF DATA-DRIVEN EARLY WARNING PERFORMANCE EVALUATION INDICATORS AND CALCULATIONS

A. EXPERIMENTAL PREPARATION

(1) Experimental Data Sources and Collection The experimental data record was collected from the measurements of 30 consecutive days of a real deep foundation pit project. The data record covers the main construction period of deep foundation pit project, including excavation, support and support replacement. The sensor network was: strain gauge (bending moment of support piles, sampling frequency 1

Hz), inclinometer (horizontal displacement, 0.5 Hz), axial force gauge (support axial force, 0.2 Hz), hydrostatic level (surface settlement, 0.1 Hz). There were about 5.2 million raw data in total from 12 measuring points with 4 types of sensors. The data record included the support structure abnormal deformation trend manually inspected on day 8, 17 and 24.

(2) Experimental Environment and Tools The experiment was conducted on an industrial PC equipped with an Intel Core i7-12700 CPU and 32GB RAM. The data fusion and early warning algorithms were implemented using Python 3.9, with Kalman filtering using the filterpy library and grey relational analysis based on a custom NumPy implementation. Data visualization was performed using matplotlib and pyecharts.

B. COMPARATIVE EXPERIMENT OF MULTI-SOURCE DATA FUSION EFFECT

To verify the effectiveness of the multi-source data fusion method, 30 days of on-site sensor data from a deep foundation pit project were selected, including four types of sensors: strain gauges, inclinometers, axial force gauges, and hydrostatic levels. The sampling frequency ranged from 0.1 to 1 Hz, with a total data volume of approximately 5.2 million records. Three comparison groups were set up: no fusion (single sensor), simple averaging fusion, and the method proposed in this paper, to evaluate the effective data retention rate, signalto-noise ratio, and root mean square error.

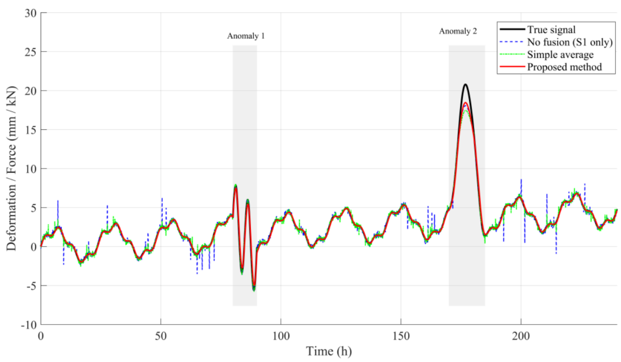

FIGURE 1. Comparative Evaluation of Multi-Source Data Fusion Effect

As shown in Figure 1, the adaptive weighted fusion method combined with Kalman filtering demonstrates significant effectiveness in multi-source data fusion. Compared to no fusion (single sensor) and simple averaging fusion, the proposed method achieves an effective data retention rate of 98.3% (defined as the ratio of valid data points remaining after outlier removal and interpolation to the total number of raw sampling points), an increase in signal-to-noise ratio to 20.3 dB (defined as the ratio of the power of the fused signal to the power of the residual noise), and a reduction in root mean square error to 0.34 (28.3% lower than simple averaging). This method effectively suppresses noise, fills in lost packets, and retains abnormal features, providing high-quality data support for subsequent early warning.

C. COMPARATIVE EXPERIMENT ON EARLY WARNING TIMELINESS AND ACCURACY

To evaluate the performance of the improved grey relational analysis combined with the dynamic threshold three-level early warning model proposed in this paper, three comparison groups were set up: the fixed threshold method, the single-source dynamic threshold method, and the method proposed in this paper. Based on 30 days of on-site measured data of the same foundation pit (including abnormal deformation trends of the support structure confirmed by three manual inspections), the early warning response time, false alarm rate, and number of early identifications for each method were statistically analyzed.

TABLE 3. Comparative Evaluation of Early Warning Timeliness and Accuracy

Warning Method	Response Time (s)	False Alarm Rate (%)	Early Detection Count (times)
Fixed Threshold Method	125.3	32.5	1
Single-Source Dynamic Threshold Method	68.7	18.2	2
Proposed Method	4.2	8.6	3

In Table 3, the early warning response time of our proposed method is only 4.2 seconds, which is 121.1 seconds shorter than the fixed threshold method and 64.5 seconds shorter than the single-source dynamic threshold method; the false alarm rate is 8.6%, which is 23.9 percentage points lower than the fixed threshold method and 9.6 percentage points lower than the single-source dynamic threshold method; for the three real abnormal trends, our proposed method achieved early identification in all cases, with an average early detection time of 2.4 hours. This indicates that multi-source fusion data and the improved grey relational analysis model can significantly improve the timeliness and accuracy of early warnings.

VII. CONCLUSION

This study proposes a safety early warning method for deep foundation pit support structures based on multi-source sensing and real-time data fusion. By integrating strain gauges, inclinometers, axial force gauges, and hydrostatic levels, a comprehensive monitoring network was established. The research demonstrates that the combination of adaptive weighted fusion and Kalman filtering effectively handles heterogeneous data, significantly reducing noise and improving signal quality. Furthermore, the improved grey relational analysis, which incorporates a time weight factor and dynamic thresholds, provides a robust framework for identifying potential failure modes in real-time. Experimental results confirm that the proposed system achieves high accuracy with a 98.3% data retention rate and a rapid response time of 4.2 s. This approach enhances the reliability of safety monitoring in complex underground construction environments, offering a valuable tool for risk mitigation in deep excavation projects.

AUTHOR CONTRIBUTIONS

Yuxiang Zhang designed, collected and analyzed the data, and drafted the manuscript. Yuxiang Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yuxiang Zhang 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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