Monitoring Information Pre-warning System of Foundation Pit Engineering Based on Human Brain Cortex RBF Neural Network

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ABSTRACT

For the requirements of information, integration and sharing of foundation pit monitoring, a monitoring information pre-warning system of foundation pit engineering based on human brain cortex RBF neural network Kalman filtering algorithm has developed on the Revit platform. The neural network algorithm is embedded in the system to achieve scientific pre-warning of system through the powerful de-noising function of human brain cortex RBF neural network Kalman filtering algorithm. At the same time, the system also boasts functions, such as storage, processing, analysis, and inquiry of monitoring information and automation output. The system relies on the Revit platform to realize information sharing and multi-person cooperation, which improves the running efficiency under the network environment and provides a powerful information platform for foundation pit monitoring.

Key Words: Human Brain Cortex RBF Neural Network, Kalman Filtering Algorithm, Pre-warning System, BIM Integrated Management

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Introduction

In recent years, with the rapid development of China's economy, high-rise buildings in cities have gradually increased and high-rise buildings have also raised higher and higher technical requirements for foundation pit construction. In order to ensure the safety of foundation pits and adjacent buildings during foundation pit excavation and construction, effective on-site monitoring measures shall be taken during foundation pit construction (Su and Chong, 2007; Saxena and Saad, 2007). In addition, to ensure the safety of foundation pit construction, we must give full play to the monitoring results and realize the rapid and accurate collection, scientific analysis and feedback of all kinds of monitoring data and related information. Monitoring results shall be shared and communicated among various departments. A powerful monitoring information management platform based on BIM shall be established so as to realize integrated management of all kinds of monitoring data and related information. Besides, deep-level processing and analysis shall be carried out on this basis so as to guide construction and optimization design (Rafiee *et al*., 2007).

The monitoring information management platform is an important part of foundation pit information construction. At present, the existing foundation pit monitoring information management platforms mainly include the foundation pit monitoring data management system introduced by Zhang Youliang *et al*., the foundation pit monitoring information management system introduced by Hu Youjian *et al*., that has integrated pre-warning function;

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and the foundation pit monitoring information management system based on web introduced by Xie Wei *et al.*, who presented the design method. However, the following problems commonly exist in these foundation pit monitoring information management systems:

(1) The researches focus on the realization of basic functions such as management and query of monitoring data, but lack integrated management of measuring point information, monitoring instrument, and surrounding buildings (Dornfeld and Devries, 1990). If there is no specific foundation pit background, simple monitoring data is meaningless.

(2) Some systems realize the drawing and management of monitoring point layout and surrounding site but this is not based on BIM, so it is impossible to effectively establish the correlation between monitoring data and 3D model.

(3) Effective monitoring data analysis is insufficient. Whether the monitoring data is effectively analyzed is an important means to predict the safety risk. Most of the existing monitoring systems achieve the safety pre-warning effect by setting the safety pre-warning value through experience (Salles *et al.*, 2000). However, in the construction process, the systems may cause false alarm due to abrupt change of monitoring value caused by on-site construction. Therefore, how to use scientific methods to filter these abrupt-changed monitoring values caused by accidents is a key problem to be solved in foundation pit monitoring.

(4) The output of monitoring results has not been introduced. The timeliness of foundation pit monitoring is very strong, which requires that the monitoring data can be processed and analyzed in a timely manner. However, the production of monitoring reports is very time-consuming and energy-consuming. If the automatic output of monitoring reports can be realized, the work efficiency and information feedback level will be greatly improved.

BY analyzing the problems in the existing foundation pit monitoring information management systems, the author develops a distributed foundation pit monitoring information pre-warning system based on BIM, which can realize monitoring data sharing and cooperative work, and comprehensively collects relevant data of measuring point information, monitoring instrument, monitoring data and surrounding buildings. On this basis, this system can realize the functions of information storage, analysis and processing, automatic output of results and pre-warning.

System Structure Design

The main goals that the system needs to achieve are as follows:

(1) To develop BIM from the bottom layer, to realize the functions of graphic display, graphic and attribute association and visual inquiry, and to achieve the storage and integrated management of foundation pit measuring point information, monitoring instrument, monitoring data, surrounding building information and other related materials.

(2) To achieve multifunctional information query, including query of monitoring data, instrument attributes, survey design data, and geographic information.

(3) To achieve functions of monitoring and pre-warning. Kalman filtering algorithm technology is used to realize de-noising and scientific pre-warning of monitoring data. The error contained in monitoring data due to construction conditions, climate conditions and measuring instruments is filtered by the model so that the pre-warning of the system is more scientific and accurate.

(4) To realize centralized management and distributed application. On the one hand, it can carry out centralized management for several foundation pit monitoring projects on one platform. On the other hand, it can meet the need of operation under the network environment and realize resources sharing and multi-person cooperative work. It conducts hierarchical management within the system, and personnel of different levels can operate within the authority at the same time (Xiaoli *et al.*, 1997.).

Monitoring Pre-warning System Based on Neural Network Algorithm

Artificial neural network is a research field of computing science and bionics arising in recent years. By studying it, people try to discover the mystery of human brain and establish an intelligent system that can simulate the function and structure of human brain so that computer can process information like human brain. The essence of human brain cortex RBF neural network reflects a mathematical expression of transformation from input to output. This mathematical relation is determined by network structure that must be designed and trained

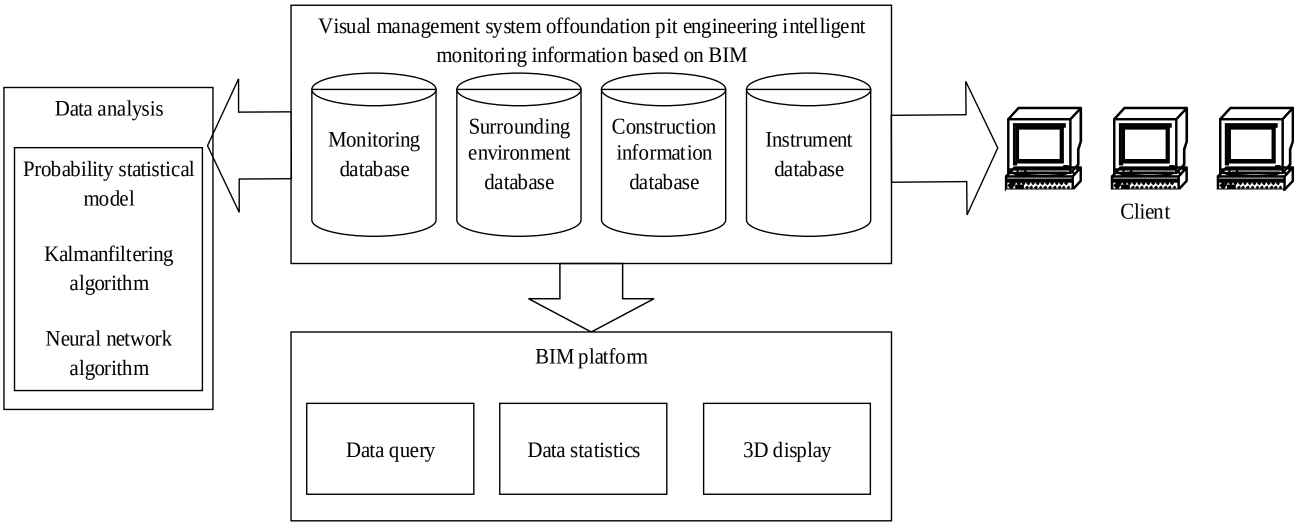

Figure 1. The structure framework of system

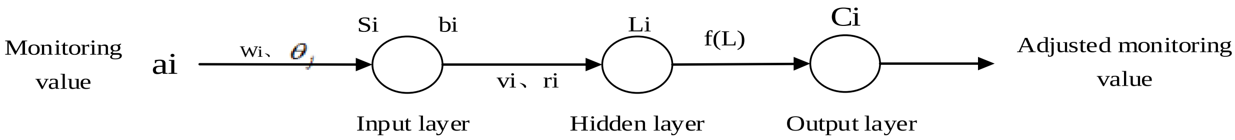

Figure 2. Working principle of human brain cortex RBF neural network

according to specific problems (Hong *et al*., 1996; Yuan *et al*., 2005; Scala *et al*., 1996).

The monitoring data is de-noised to ensure the accuracy by the Kalman filtering algorithm based on the principle of human brain cortex RBF neural network which is an optimized data filtering algorithm in time domain. The dynamic change law of the signal is expressed by kinetic equation and the observation data is updated in real time by recursive way to obtain the new Kalman filtering value, namely, the de-noised monitoring value. The modeling process is simple and the speed of data calculation is fast.

Human brain cortex RBF neural network algorithm

The human brain cortex RBF neural network stimulates the neural system structure of the human brain with the functions of self-learning, nonlinear mapping and associative memory so that it can be used to conduct modeling for the nonlinear system. Through training and learning, the human brain cortex RBF neural network can learn the state transition matrix F of Kalman filtering.

In the human brain cortex RBF neural network, the independent variable signal propagates forward from the input layer to obtain the output value through weighted sum in the hidden layer. The error between the output value and the desired output value is distributed to each node of each layer to correct the next output. Three-layer (input layer, hidden layer, output layer) human brain cortex RBF neural network can identify any kinetic equation as a nonlinear system.

Human brain cortex RBF neural network is a single-input and single-output system. The number of neurons in both input and output layers is 1 and the number of neurons in the hidden layer follows the law of 2n+1. The number of nodes in the hidden layer is set to be 3 and the working principle of a neuron is as shown in Figure 2. After a_i is input into the input layer, the weight coefficient w_i and the output threshold value θ_i are integrated to obtain the input variable s_i of the middle layer, as shown in formula (1).

$$s_i = w_i a_i - \theta_i \tag{1}$$

The output variable b_i of the middle layer is obtained by formula (2).

$$b_i = \frac{1}{1+e^{-s_i}} \tag{2}$$

The input value of the output layer unit of the neural network L_i is calculated according to the connection weight v_i from the middle layer to the output layer and the output threshold value γ_i:

$$L_i = v_i b_i - \gamma_i \tag{3}$$

Finally, the output value of the neural network C_i is calculated according to the output value L_i, and the calculation formula is:

$$C_i = f(L_i) = \frac{1}{1+e^{-Li}} \tag{4}$$

The error between the output value and the desired output value is distributed to each node of each layer to correct the next output. After manifold cycles, the exact weight and threshold value in each layer are obtained. In addition, the transition function of each layer of the system is also known, so the state transition matrix F of the Kalman filtering system can be determined.

Kalman filtering algorithm

After obtaining the dynamic transition matrix F of Kalman filtering, the observation equation of the system is shown in formula (5).

$$X_{k+1|k} = FX_{k|k} \tag{5}$$

Where, $X_{k+1|k}$ indicates the estimation state at the next time point, $FX_{k|k}$ represents the current prediction state, and F is the state transition matrix.

$$P_{k+1|k} = FP_{k+1|k+1}F^T + GQG^T \tag{6}$$

Where, $P_{k+1|k}=FP_{k+1|k+1}F^T+GQG^T$ represents the covariance matrix of estimation value at the current time point, and Q represents the covariance matrix of the system noise.

Through formula (7), the Kalman filtering gain is used to judge the weight of the BP neural network model and the actual measured value in the Kalman filter to achieve the purpose of filtering.

$$K_{k+1} = P_{k+1|k}H^T[HP_{k+1|k}H^T + R]^{-1} \tag{7}$$

Where, K_{k+1} represents the Kalman filtering gain, H represents the system observation matrix, and R represents the covariance matrix of the measured noise.

After obtaining the Kalman filtering gain, the optimal Kalman filtering value can be obtained by formula (8), and the covariance matrix for the next iteration is obtained by formula (9):

$$X_{k+1|k+1} = X_{k+1|k} + K_{K+1}(Y_{K+1} - HX_{k+1|k}) \tag{8}$$

$$P_{k+1|k+1} = [I_n - X_{k+1}H]P_{k+1|k} \tag{9}$$

Where, $X_{k+1|k+1}$ represents the optimal Kalman filtering value, and $P_{k+1|k+1}$ represents the estimation covariance matrix at the next time point.

Through Kalman filtering processing, the influence factors such as construction, field environment and instrument measurement accuracy in monitoring can be filtered out to restore the real monitoring value so as to make the monitoring data more accurate.

Other Functions of System

Database management

The database of the system can be divided into: instrument file information database, monitoring database, geographic information database, daily file database and other related information database by categories. The monitoring database is divided into attribute information database and monitoring information database according to functions (Kim and Yoon, 2010). These databases are linked through key fields, which are the basis for querying and in-depth data analysis.

The structure design of database is the core of the system. In order to effectively manage the hierarchical relation of foundation pit monitoring objects, five hierarchies are designed, including engineering project, section, group (measuring point set of the same monitoring item located under a certain borehole or a certain section), monitoring item and measuring point. And a tree list is adopted to describe and organize the database so that each measuring point has a clear affiliation. These five kinds of objects have their different attributes, which constitute the attribute database, and establish the affiliation between the monitoring points of foundation pits and the monitoring items, as well as between the objects, which makes it convenient for management and inquiry (Burke and Rangwala, 1991; Laskaris *et al.*, 1997). In addition, the system provides the functions of add, delete and modify for objects, and the system can also store documents, pictures, video and audio materials. Figure 3 is the management interface of the monitoring system.

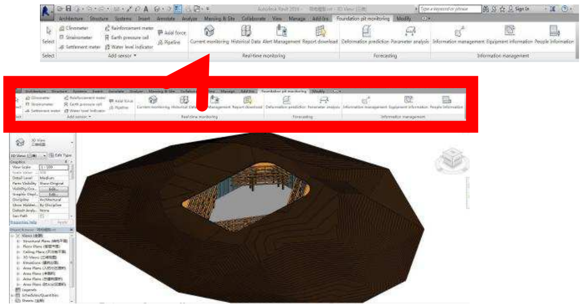

Figure 3. Management interface of foundation pit monitoring system

Monitoring data processing

Foundation pit monitoring can be divided into two types according to monitoring object: foundation pit enclosure system and surrounding environment monitoring. Foundation pit enclosure system mainly includes inclination of enclosure wall, horizontal and vertical displacement of enclosure wall top, support structure crack, pile stress, support axial force, underground water level, pore water pressure, soil pressure, foundation pit spring back, vertical and horizontal displacement of deep soil. The surrounding environment monitoring mainly includes the settlement and inclination of buildings (structures), vertical and horizontal displacement of underground pipelines, surface soil settlement and cracks of buildings and surrounding roads.

The developed system realizes the function of data collection and management commonly seen in foundation pit monitoring items, including inclination, horizontal displacement, settlement, pile stress, support axial force, soil pressure, and underground water level. The system collects and processes the monitoring data, and converts physical quantity according to the specifications and regulations of foundation pit monitoring. At the same time, the system also has the functions, such as basic data statistical analysis, process curve drawing, measuring point distribution curve and correlation curve drawing (Wang and Cui, 2013). Through the correlation curve, we can visually analyze the change of monitoring data with the construction progress. Figure 4 is the process curve drawing interface.

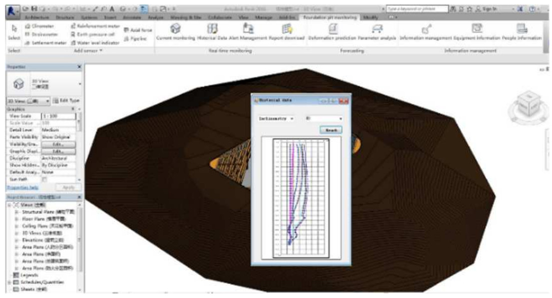

Figure 4. Historical data query

Automatic output of monitoring report

The system can realize the automatic output of the monitoring report. Through the built-in monitoring item template of the system, we only need to input the date range and set the monitoring items, sections or measuring points contained in the report so that the system can automatically search and extract data to generate tables and curves in the monitoring report so as to generate Word documents, as shown in Figure 5.

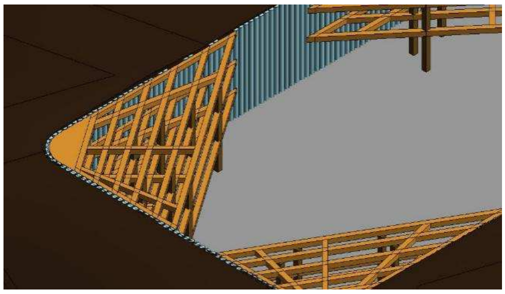

Figure 5. Automatic output of monitoring report

Multifunctional information query

The system conducts integrated management for monitoring data, construction progress, instrument attributes, survey design data, graphics, and daily files, providing powerful query functions for convenient access to specific information for users, such as monitoring value query, monitoring instrument attribute query, and daily file query, geographic information query and workload information query, and so on. All queries do not require users to input SQL statements themselves because the system is highly encapsulated. Users just need to select the query methods according to their habits and add the query conditions. Then the SQL statements will automatically generate according to the users' settings to realize complex multi-table cross-combination query function.

Conclusions

This study has introduced the design method and main functions of the distributed foundation pit monitoring information management and pre-warning system based on BIM developed by the author. Compared with other foundation pit monitoring systems, this system boasts the following advantages:

(1) Integrated management of information
The system realizes centralized storage and integrated management of measuring point information, monitoring instruments, monitoring data, surrounding building information on BIM platform instead of simple management of monitoring data, achieving cooperative work of monitoring personnel and information sharing of various departments.

(2) BIM visualization
The system realizes data input, drawing, display and BIM association between data and monitoring object, and then realizes visual query of monitoring information in BIM.

(3) Modular development
For all kinds of foundation pit monitoring items, the system provides modules of corresponding attribute information, monitoring data transmission processing, analysis, curve drawing and report output respectively so as to facilitate the expansion of monitoring items. The system also provides rich information inquiry functions and many kinds of data analysis and pre-warning models to ensure the construction safety of the project.

(4) Scientific pre-warning function
The system uses human brain cortex RBF neural network Kalman filtering algorithm technology to realize monitoring data, filtering and pre-warning. The error contained in monitoring data due to construction conditions, climate conditions and measuring instruments is filtered by Kalman filtering algorithm so that the pre-warning of the system is more scientific and accurate.

(5) Automatic report output
The system realizes automatic output of monitoring report and improves the output efficiency of monitoring results so that the monitoring data can be processed and analyzed in time.

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