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A multilevel computational research method integrating non-contact impact echo acoustic-frequency method and BIM technology in health monitoring of human defense projects

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Abstract Human defense engineering is an important part of building design, in order to further improve the quality of human defense engineering design in construction projects, this study introduces BIM technology and non-contact impact echo acoustic frequency method into the health monitoring of human defense engineering. Based on BIM technology, a quality monitoring system for human defense project is designed to realize the comprehensive supervision and control of the quality of human defense project. Then the impact echo acoustic frequency method is combined with YOLOv2-Tiny algorithm to construct the discriminative technology for health monitoring of human defense projects. It is found that the discrimination technology can accurately identify the defect type and location, and the overall prediction accuracy reaches more than 96%. At the same time, the application of BIM technology in the case study avoids the problems in the construction design of the civil defense project and guarantees the construction quality of the civil defense project, and the error between the thickness of the steel pipe concrete member obtained by the proposed discriminative technology and the actual one is less than 2.81%.The fusion of the BIM technology and the impact echo acoustic-frequency method provides a brand-new solution for the quality supervision of the civil defense project.

Index Terms BIM technology, YOLOv2-Tiny, impact echo acoustic frequency method, human defense project, health monitoring

I. Introduction

People's air defense basement is one of the components of the human defense project, which can be used as shopping malls, civic and sports venues, etc. in peacetime [1]. In wartime, it can be used as a shelter to provide protection for personnel, means of transportation, materials and so on [2]. Due to the special nature of the human defense project, compared with ordinary civil buildings, its construction process involves multi-dimensional, multi-specialty, multi-trade intersection, construction risk influencing factors, and the quantitative assessment of health risk is more complex [3]-[5]. Li, A et al. conducted an in-depth study on the detection methods of human defense engineering, combined with geological survey methods, accurately provided the planar distribution, scale, burial depth, trend, distribution of overlying soil layer and analysis of physical and mechanical properties of air-raid shelter, which provided technical support for the technical risk assessment of air-raid shelters and post-construction reconstruction [6]. Trout, E. A et al. pointed out that the UK had recognized the importance of human defense works in 1935 and proposed corresponding risk control measures for air raid shelters [7]. In view of this, there is an urgent need to use effective means to monitor and assess the safety status of the completed and used human defense engineering facilities, repair and control damage, to ensure the safety, integrity, suitability and durability of the engineering structure used [8].

Engineering structural health monitoring, integrating intelligent sensing elements, data wired or wireless acquisition and real-time processing, structural damage identification, health diagnosis and reliability prediction as well as remote communication and data management, and other hard- and software systems, is a symbol of the development and synthesis of engineering theories, and a sign of the development and integration of high and new technologies [9], [10]. At the same time, it is also the centralized embodiment of modern engineering structure experimental technology [11]. Structural monitoring has increasingly become an important guarantee technology for major engineering structural design verification, construction control, safe operation and maintenance management [12]. Currently, structural health monitoring has become a worldwide research hotspot. For example, Tokognon, C. A et al. implemented a framework for a structural health monitoring (SHM) system that collects and analyzes a large amount of data from sensors mounted on structures using Internet of Things (IoT) technology [13]. Bao, Y and Li, H used machine learning techniques to address the challenges of traditional vibration-based structural health monitoring methods and established a new machine learning paradigm for structural health diagnosis and prediction [14]. Barbosh, M et al. comprehensively reviewed and summarized the application of Empirical Modal Decomposition (EMD) and its variants in structural health monitoring, pointing out that EMD can be widely used for structural modal identification and damage detection, and that it is robust [15]. In their study, Dong and Catbas illustrated the advantages and disadvantages of the computer vision-based structural health monitoring (CV-SHM) technique, pointing out that CV-SHM can be applied both at the local level (e.g., detecting cracks, spalling, delamination, rust, and loosening of bolts) and at the global level (e.g., measuring displacements, analyzing structural behaviors, and identifying vibrations, modal properties, and damage) [16].

In recent years, with the development of non-destructive testing (NDT) technology, the impact echo acoustic frequency (IAE) method based on acoustic characterization has been investigated and applied in the health monitoring of engineering structures [17]. IAE method is an effective method to discriminate the defects of engineering structures by stimulating the sound signals by knocking, using wide frequency domain and high pointing pickup device to pick up the sound signals and analyzing them by machine learning means to determine the defects of concrete structures [18], [19]. The IAE method combines the advantages of both the manual tapping method and the impact echo (IE) method, and at the same time solves the problem that the vibration pickup sensor needs to be fixed on the surface of the measured body in the impact echo method, which has higher detection efficiency and consistency [20].

The study discusses the human defense engineering and its health monitoring method, and analyzes the nondestructive testing method of construction engineering combined with impact echo acoustic frequency technology and BIM technology. Then, the BIM technology is utilized to construct a quality monitoring system for human defense engineering, and its architecture design and software design are studied, and the three parts of the data acquisition and processing layer, the BIM model integration layer, and the quality monitoring and control layer are discussed. Subsequently, the YOLOv2-Tiny algorithm in transfer learning is introduced to be combined with the impact echo acoustic-frequency method in order to improve the resolution efficiency of human defense project quality discrimination and the objectivity of the results. The tunnel lining defect pictures of a high-speed railroad are selected as the dataset, and the model is trained and tested to explore its recognition accuracy under different quality defects and different iteration times. Finally, the results of the application of BIM technology and impact echo acoustic frequency method are analyzed by taking a person's defense project as an example.

II. Health monitoring of human defense works

In recent years, the city's rapid development of human defense projects, the country continues to emerge focusing on the integration of large-scale underground space projects, but with the vigorous promotion of human defense project construction, more and more problems have been exposed. First of all, the human defense project is mostly an underground project, in the construction and construction process by many conditions, the building structure space is limited. Secondly, it is difficult to implement the conversion of civil defense projects in the design. In order to solve the above problems, it is necessary to introduce new technologies into the human defense design process. Building Information Modeling (BIM) technology, as an emerging informatization technology in the construction industry, is the best solution to this problem as it can fully record and transfer project information without any loss during the whole life cycle of the project.

II. A.Human defense works

Human defense works, also known as civil defense works, refer to underground protective buildings built separately to safeguard wartime people's air defense command, air defense services, personnel and material sheltering, medical rescue and so on, as well as basements built in conjunction with ground-level buildings that can be used for air defense in wartime. The uniqueness of human defense works lies in their ability to protect against conventional, nuclear, biological and chemical weapons strikes and shock waves, and their resistance and protection level are regulated by the state according to the war pattern and the intensity of weapons strikes with tactical and technical requirements. The State has strict requirements for the area, grade, function, design and construction of human defense works, and has various classification schemes, the most common way at this stage is to classify them by their wartime function.

II. B.Health monitoring methods

In order to cope with the demand for the construction and quality monitoring of human defense projects more and more construction units began to pay attention to the introduction of various new technologies in the process of engineering construction. NDT technology has the advantages of convenience, accuracy and not causing damage to the internal structure of the construction project, and has been widely favored in the field of quality inspection of construction projects.

NDT technology is mainly divided into two categories: one is conventional NDT technology, including visual inspection method, radiographic method, ultrasonic NDT technology and so on. The other category is non-conventional NDT technology, including infrared imaging detection technology, electromagnetic induction NDT technology, impact echo NDT technology and so on. In addition, NDT technology based on BIM (building information modeling) technology and artificial intelligence technology is a new member in the NDT technology team. This paper integrates the non-contact shock-echo NDT technology and BIM technology to study the health monitoring of human defense engineering.

II. B. 1) Impact-echo acoustic-frequency technology

The application of impact echo nondestructive testing technology by inspectors can accurately detect the quality of the building components in the human defense project, which can help to make up for the defects of ultrasonic nondestructive testing technology and infrared imaging detection technology. Detectors can accurately assess the thickness of the concrete structure through the size of the reflected wave, the depth of defects, and can be made into a spectrogram to visualize the intensity of the fluctuations of the impact echo. The advantages of impact echo nondestructive testing technology are simple operation, reusable, and high detection efficiency.

II. B. 2) BIM and AI technologies

As a new type of non-destructive testing technology, steel structure inspection technology based on BIM technology can make the imaging clearer by de-noising the steel structure inspection imaging in the human defense project. In addition, the application of BIM technology can detect whether there is any collision or conflict between steel structures, thus improving the inspection quality. The application of artificial intelligence technology can optimize the health monitoring process of the human defense project, improve the automation level of the detection system, and thus improve the safety, efficiency and accuracy of health monitoring. The role of artificial intelligence technology is specifically manifested in the following aspects: ① Automated detection. The application of artificial intelligence technology to create an automated nondestructive testing system can effectively eliminate the interference caused by manual errors and ensure that the test results are accurate. ② Real-time monitoring and predictive maintenance. The application of artificial intelligence technology can carry out real-time monitoring of the quality inspection work, and predict potential defects through intelligent analysis, so as to facilitate the construction personnel to maintain in advance, in order to improve the quality of construction.

III. Design and analysis of health monitoring methods for human defense projects

III. A. Quality Supervision of Human Defense Project Based on BIM Technology

III. A. 1) Architectural design

Building Information Modeling BIM is a building information database formed by taking building three-dimensional informatization as a carrier, running through the whole life cycle of the building, associating the information needed for design, construction and operation and maintenance, and the collaborative work of various work types. Using BIM technology to establish a quality supervision system for human defense projects, the general framework of the quality supervision system for human defense projects based on BIM technology is shown in Figure 1, which is divided into two parts: hardware and software. The hardware includes ADXL345 series accelerometers, DHT22 series humidity sensors, two kinds of communication devices, Wi-Fi and Ethernet, embedded computing devices of PowerEdgeR740 series and Raspberry series, and hard disk drives of HDD series. The software design focuses on transforming the raw data into a format that can be used for further analysis and display through the data acquisition and processing layer, the data from the data acquisition and processing layer is received by the BIM model integration layer and integrated into the BIM model, and finally the quality supervision and control layer adopts the data from the BIM model integration layer, where the user can obtain the quality monitoring results and alarm information to supervise and control the quality of the project.

III. A. 2) Data acquisition and processing layer

The specific flow of the data acquisition and processing process is shown in Figure 2. The data acquisition and processing layer is the bottom layer of the BIM technology-based human defense project quality supervision system, responsible for collecting and processing real-time data from various sensors and data sources.

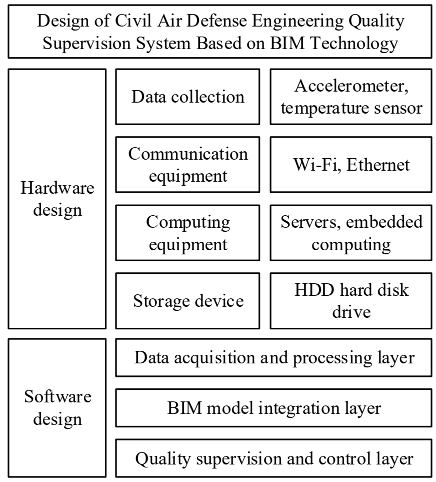


Figure 1: The framework of the civil defense project quality supervision system based on BIM

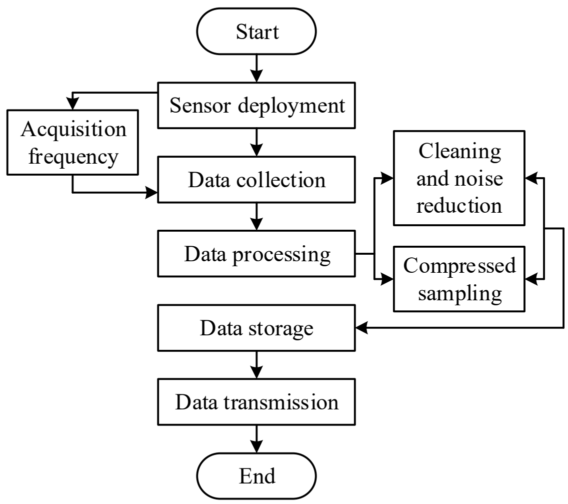


Figure 2: Data acquisition and processing flow

III. A. 3) BIM model integration layer

The BIM model integration layer is responsible for integrating real-time data from the data acquisition and processing layer into the BIM (Building Information Model) and mapping the real-time data to the corresponding locations in the building model.

(1) Model mapping and matching is the key process to correctly map the real-time data to the BIM model, matching the sensor data with the attributes of the BIM object, further mapping the collected and processed data to the corresponding parts of the building structure, using the Euclidean metric to measure the distance between the sensor data points and the attributes of the BIM object, and the formula for calculating the Euclidean metric is as follows:

$$d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{1}$$

where: $d(x,y)$ is the Euclidean distance between two points, x,y are two data points, n is the number of dimensions, and x_i,y_i are the coordinates of the two data points in the i th dimension.

The spatial distance or similarity between the sensor data points and the BIM object attributes is obtained by calculation. Finally, the timestamps of sensor data and BIM model data are made to be in the same time range by calculating the difference in timestamps. The timestamp calculation formula is as follows:

$$d(ts,tb)=|ts-tb| \tag{2}$$

where: $d(ts,tb)$ is the difference between the sensor timestamp and the BIM model timestamp, ts is the sensor timestamp, and tb is the BIM model timestamp.

Once the timestamp alignment is complete, it is necessary to find the attribute of the BIM object that is closest to the timestamp of the sensor data and use the sensor to map the data to the appropriate location in the BIM model using the corresponding timestamp.

(2) BIM integration allows two-way communication and data sharing between real-time data and the BIM model to better support engineering team collaboration and decision making.

III. A. 4) Quality monitoring and control layer

The quality monitoring and control layer, as the top layer of the system, is responsible for monitoring and controlling the quality of the human defense project to ensure the safety and compliance with the design requirements, the specific steps are as follows. (1) Quality monitoring and analysis: use NumPy data analysis library of MATLAB data analysis software to process and analyze real-time data, and use FEA finite element to establish finite element model of the structure, analyze and simulate the structural force and heat distribution, etc. (2) Security control and alarm: use GIS technology to analyze and visualize data such as geographic location and meteorology. Establish emergency notification systems such as audible alarms, red flashing lights, and emergency broadcasts to provide alerts and notifications. (3) Quality assessment and documentation: Using magnetic particle detection technology in NDT non-destructive testing, the surface of the material or structure to be inspected is cleaned and then magnetized to make it magnetic. (4) Risk management and prevention: using FMEA failure modes to identify and assess potential failure modes in engineered buildings, and by analyzing the various failure modes, determine which failures are likely to have the greatest impact on the quality and safety of the project. In summary, through techniques and methods such as data analysis, magnetic particle detection and risk management, the engineering department is able to identify problems and take preventive measures in a timely manner to ensure the sustainability and successful delivery of engineering projects.

III. B. Health monitoring based on the shock-echo acoustic frequency method

The Impact Echo Acoustic Frequency (IAE) method is significantly improved in terms of detection sensitivity, reliability, and recognition compared with the geo-radar method, but the resulting images still have to be manually recognized, which is not only inefficient but also dependent on the professional quality of the analysts, which reduces the objectivity of the results of the recognition. Therefore, this paper combines the non-contact IAE method with the migration learning algorithm to monitor and recognize the quality and health of human defense projects.

III. B. 1) IAE method

The IAE method is a relatively mature technology for detecting internal defects in concrete structures, and has been applied in many occasions, such as bridge aperture grouting compactness detection, railroad CRTS Ⅲ track plate de-voiding detection, grouting defects behind the tunnel lining detection, and concrete structural thickness detection, etc. The IAE method is based on a transient mechanical shock that generates transient low-frequency elastic waves.

The IAE method generates transient low-frequency elastic waves through transient mechanical impacts, which propagate inside the structure and are reflected back when they encounter defects or interfaces. In this process, after multiple reflections between the impact surface and the interface of internal defects and the interface at the bottom of the structure, transient resonance is triggered, and the vibration will cause the air near the surface of the structure to vibrate, which in turn generates acoustic waves. A wide-frequency domain, highly directional pickup is used to pick up the sound waves from the structure under test, which are then transmitted to a signal processor. A plot of the amplitude relationships corresponding to the frequencies in the waveform is obtained by Fast Fourier Transform (FFT) or Maximum Entropy Method (MEM), which identifies the resonance frequency in the amplitude spectrum for use in identifying and determining the location of defects in the structure.

When the pickups are close enough to the structure surface to ignore small volume differences and the air vibration is synchronized with the structure surface vibration, the acceleration of the air can be considered to be approximately the same as the acceleration of the structure surface. The relationship between the air acceleration and the air pressure difference is:

$$\rho_0 \frac{\partial v(x,t)}{\partial t} = -\frac{\partial P^{'}(x,t)}{\partial x} \tag{3}$$

where: ρ_0 is the initial stationary air density, t is a moment in the air vibration process, $P'(x,t)$ is the air pressure difference at the current moment, and $v(x,t)$ is the air flow velocity at the current moment.

The thickness of the structure can be determined based on the main frequency and main frequency drift of the collected measured frequency domain curve. The thickness of the structure is calculated by the formula:

$$T = \frac{v_p}{2f} \tag{4}$$

where: T is the calculated value of the thickness of the structure (m), v_p is the apparent wave velocity of the structure (m/s), and f is the main frequency corresponding to the thickness of the structure (Hz).

The IAE method acoustic frequency map can visualize the thickness and internal defects of the structure.

III. B. 2) Transfer learning

In order to improve the analysis efficiency and objectivity of the IAE method, migration learning in artificial intelligence is used to solve the problem of the type and location of defects in the IAE resolution map. Migration learning can borrow the already trained deep learning model (such as neural network model), use the new labeled data to train the model on the final classification layer, and then get a new model, that is, realize the migration of the model, so it is called migration learning. In this paper, we adopt the migration learning based on YOLOv2-Tiny model, which first deletes the classifiers of the source model, adds new classifiers, and then fine-tunes the new classifiers on a customized dataset.

(1) Network structure

YOLOv2-Tiny is a lightweight version of the YOLOv2 algorithm, a network model optimized for scenarios with limited computational power such as embedded devices. Compared with YOLOv2, the YOLOv2-Tiny network structure is simpler, and the YOLOv2-Tiny network structure contains nine convolutional layers and four pooling layers. In addition, YOLOv2-Tiny also adds a priori frames, BN layers, etc. to improve the detection accuracy and speed.YOLOv2-Tiny improves the detection speed without sacrificing too much of the detection accuracy, which can satisfy some application scenarios with high real-time requirements.

(2) BN layer calculation

YOLOv2 adds a BN layer in front of the activation layer behind each convolutional layer. The BN layer mainly standardizes the data before each input layer of the neural network, for example, normalizing the data into a standard normal distribution with mean 0 and variance 1. The BN reduces the model's sensitivity to the input data, which can help to reduce the risk of overfitting. The BN is normalized by the moving average mean and variance on the training set to ensure the model's generalization. Normalization is performed to ensure the generalization ability of the model.

The input data lines are first preprocessed with approximate whitening as shown in equation (5):

$$\hat{x}^{(k)} = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{Var[x^{(k)}]}} \tag{5}$$

Introduce the learnable parameter γ, β to recover the simply normalized data out to the original features of a particular layer. Let $\gamma^{(k)} = \sqrt{Var[x^{(k)}]}, \beta^{(k)} = E[x^{(k)}]$ then Eq. (6) can be expressed as:

$$y^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)} \tag{6}$$

The computational process of the BN layer can be summarized as follows: first calculate the sample mean and variance, then do the normalization of the sample data, and finally do the panning and scaling as shown in Eqs. (7), (8), (9), and (10):

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \tag{7}$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B) \tag{8}$$

$$\hat{x} \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \grave{o}}} \tag{9}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i) \tag{10}$$

where $E[x^{(k)}]$ is called as the sliding mean, which is the mean of each batch of training data $x^{(k)}$, $Var[x^{(k)}]$ is the sliding variance, m is the mini-batchsize, and ε is a very small value preventing the division by zero. γ denotes the scaling factor, and β denotes the translation factor.

(3) Prior Frames

Five a priori frames are introduced in YOLOv2-Tiny, and these a priori frames size values are obtained by clustering the target frames in the training set with the K-means algorithm. The main purpose of these prior frames is to set the initial values of the length and width of each prediction frame, which makes the training easier to converge and speeds up the training.Each cell in YOLOv2 is responsible for predicting 5 prior frames, which are centered in the current cell.YOLOv2 predicts the confidence of the target, as well as its category probability and location, based on each prior frame. The use of multiple a priori boxes helps to detect targets of different sizes and aspect ratios, thus improving the detection performance. Also, the prior frames in YOLOv2 can be optimized by re-clustering them to better fit the distribution of targets in the training set.

YOLOv2-Tiny moves and scales the a priori frames to get the prediction frames through continuous training and learning, making the prediction frames constantly close to the real frames.

III. C. YOLOv2-Tiny-IAE monitoring performance

Combined with the data of a high-speed railroad section 8 in the human defense project, the IAE method and YOLOv2-Tiny algorithm are used to identify the lining defects of the railroad tunnel. The main processes are as follows:

III. C. 1) Customized datasets and annotation

The 200 sample high-speed railroad section 8 tunnel lining IAE defect pictures collated in the preliminary stage are used as training samples and test samples for model training and ten-fold cross-validation.

The dataset is divided into 10 parts, and 9 of them are used as training data and 1 as test data in turn to conduct experiments, and then the average value is finally obtained as an estimation of the accuracy of its algorithm. The identification of the tunnel lining defects is done using the sprite annotation assistant, and finally the xml file corresponding to the image is output. The content of the xml file contains the type of defects and the corresponding location.

III. C. 2) Predefined parameters

Predefined parameters: ① Dimensions of YOLOv2-Tiny model w (width) × h (height) = 416 pixels × 416 pixels. ② The model is in color, so the number of channels of the image is set to 3. ③ The YOLOv2-Tiny model splits the image width and height into 13 equal parts each. ④ The type of structural defect is set to 4. ⑤ The number of training iterations is 500.

III. C. 3) Training algorithms

The training algorithm uses the Non-Maximum Suppression (NMS) method. This algorithm avoids the problem of the same region being recognized many times over.

III. C. 4) Model accuracy analysis

According to the results of ten-fold cross-validation, the overall defect recognition accuracy of the training model obtained from migration learning exceeds 96%. However, there are still some errors due to the influence of uneven sample distribution and the number of iterations.

(1) Uneven sample distribution

Because the ultra-thick or insufficient strength samples exceed 1/4 of the total number of samples, resulting in sample imbalance, making the judgment results more skewed in favor of this type of defects. The final training results also confirm this.

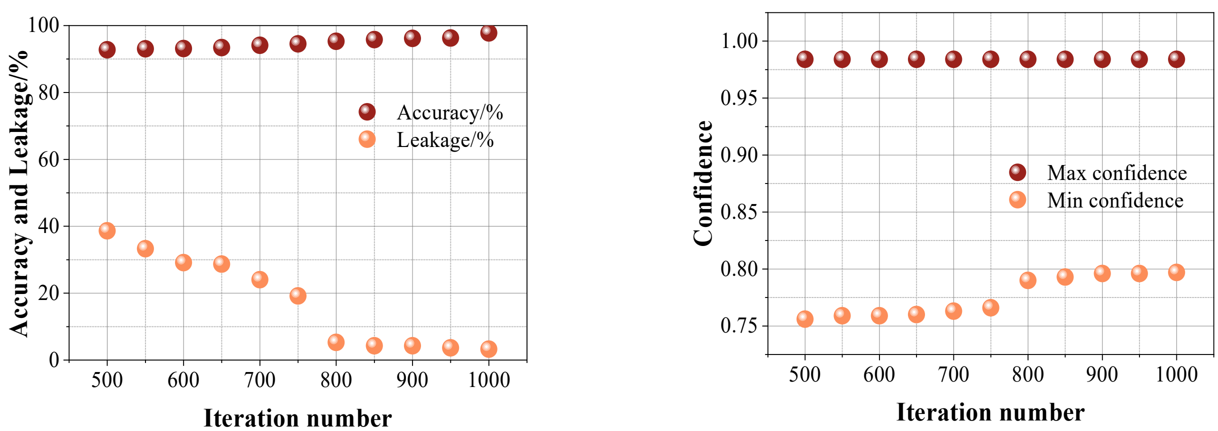
The number of iterations and the accuracy rate of each type of defects are shown in Table 1. It can be seen that: when the number of iterations increases from 500 to 1000 due to the large number of training samples for the over-thickness or under-strength defects, the accuracy rate of the defects is as high as 100%, whereas the accuracy rate of the other 3 types of defects only increases from the lowest 92% to 96% due to the insufficient number of training samples. The vast majority of misclassifications were for other types of defects, especially deep dehollowing which was misclassified as overthickness or understrength.

Table 1: The number of iterations and the accuracy of all kinds of defects

Iteration number	Defect type	Accuracy/%	Iteration number	Defect type	Accuracy/%
500	Overthickness or insufficient strength	100	750	Underdensity	95
500	Not thick enough	93	750	Dislodge	96
500	Underdensity	92	1000	Overthickness or insufficient strength	100
500	Dislodge	94	1000	Not thick enough	97
750	Overthickness or insufficient strength	100	1000	Underdensity	95
750	Not thick enough	96	1000	Dislodge	96

(2) Number of iterations

The curves of underthickness defect accuracy, leakage rate, and confidence level with the number of iterations are shown in Fig. 3. It can be seen that: increasing the number of iterations for model training has a significant effect on improving the leakage rate. When the number of iterations increases from 500 to 1000 the accuracy increases from 92.75% to 97.79%, the leakage rate decreases from 38.63% to 3.27%, the minimum confidence level increases from 0.756 to 0.797, and the maximum confidence level remains at 0.984.



(a)Accuracy and leakage rate

(b)Confidence degree

Figure 3: The change curve of accuracy, leakage rate, confidence degree

IV. Analysis of examples

In the previous section, this paper designs the health monitoring method of human defense engineering based on BIM technology and non-contact impact echo acoustic frequency method, and the following is an example analysis of integrating these two methods for health monitoring of human defense engineering.

IV. A. Project overview

This project is an underground two-storey civil defense project, with a total construction area of 25764.23 square meters and a civil defense area of 22407.15 square meters. It functions as commercial and supporting facilities in normal times. In wartime, it functions as a war reserve material storehouse and an evacuation channel. It is centrally set up in the lower part of the road of Wei XII Road, from Jing X Road in the south to Jing Qi Road in the north. Combined with the existing urban layout of the region, commercials are set up in the first underground layer of the whole section from Jingyi Road to Jingx Road and the second underground layer of the section from Jingqi Road to Jingx Road, which attracts people to enter the underground through the ground crossing and facilities such as ground entrances and exits, eases the pressure of the ground pedestrian traffic, and connects with the neighboring commercial facilities to give full play to the commercial advantages of the lot.

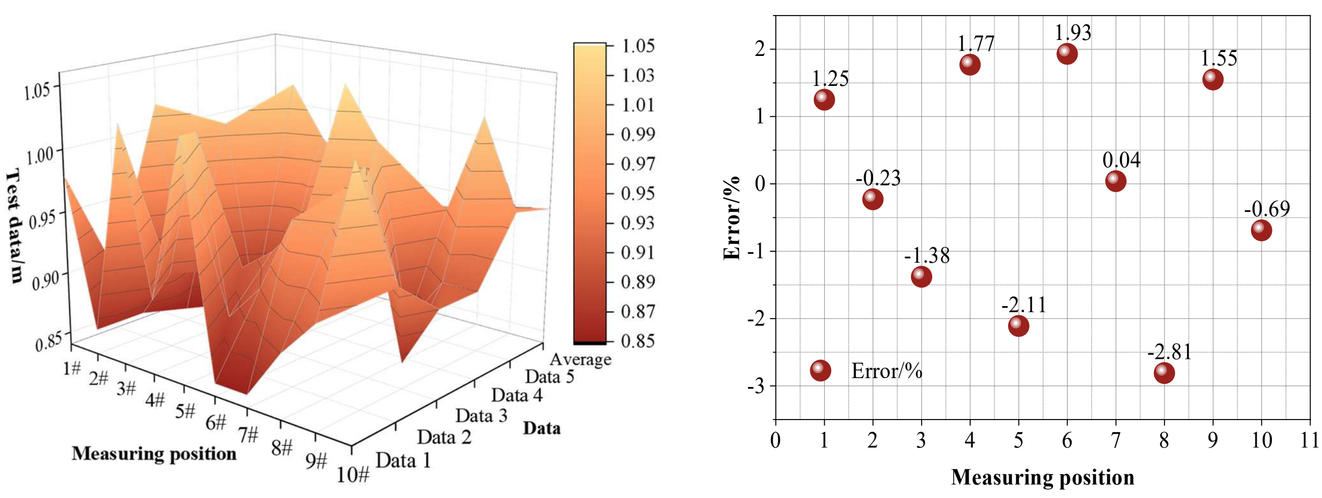
Firstly, the quality supervision system of human defense project based on BIM technology is applied to supervise and manage the design of this project, and then the health monitoring model based on non-contact impact echo acoustic frequency method and migration learning is applied to identify the defects of steel pipe concrete components.

IV. B. BIM application results

The BIM practice in the case of human defense project has achieved certain results, which are mainly reflected in the following 2 aspects: the first aspect is to find out the design problems in the original drawings through the BIM model, such as the conflict between the human defense door and the ventilation pipeline in the No. 5-6 human defense entrance, the collision between the ducts and the finishes ceiling in the No. 4 exhaust room, and so on, and to optimize the drawings in advance, so as to avoid the problem of changes in the course of the construction. The second aspect is the special optimization of the pipeline construction with the relevant installation units before the equipment pipeline layout based on the model, especially to ensure the project headroom and compression of about 1/3 of the electromechanical installation period, in addition to optimizing the pipeline routing, reduce the pipeline materials. The net height of the central area of the project is effectively controlled to ensure that the net height of the commercial area is above 3.5m, which is highly praised by the construction side.

IV. C. Impact echo test results

In order to test the feasibility of impact echo acoustic frequency method for detecting a steel pipe concrete member of the case human defense project, a portable instrument of CTG-1T series developed by Olson Company was used to collect data, and the impact echo meter was used to select points for measurement in the important parts, and 10 measurement points were selected for detecting the steel pipe concrete, with the measurement points of #1# - #5# spread on the upper end of the steel pipe of 1/8 span - 1/4 span, respectively, and the measurement points of #6# - #10# located between 1# column and 2# column. The impact echo test data and errors are shown in Figure 4. From the field impact echo results, the result analysis shows that the impact echo test results of the steel pipe concrete members are stable, and the difference between the measured thickness and the theoretical thickness is less than 2.81%. When measured, the waveform peak is obvious and the signal realism is high. Figures 5 and 6 are the time-domain curve and frequency-domain curve of the impact echo test at measurement point 3#, and the peak value of the signal at measurement point 3# is obvious, which indicates that there are not too many defects during the propagation process of the stress wave, and the quality of the concrete inside is dense. Figures 7 and 8 are the time domain curve and frequency domain curve of the impact echo test at 8# measurement point, the signal at 8# measurement point has more than one peak, indicating that the stress wave propagation process encounters defects generated by diffraction, scattering and reflection back to the peaks generated by the concrete may have slight quality problems.



(a)Test data (b)Error

Figure 4: Data and error of shock echo test

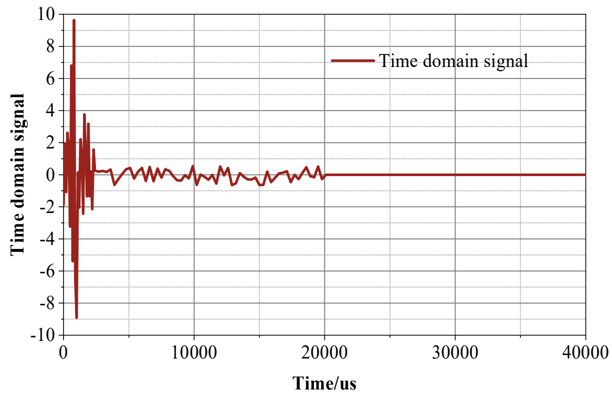


Figure 5: The time domain curve of a measuring signal of 3# point

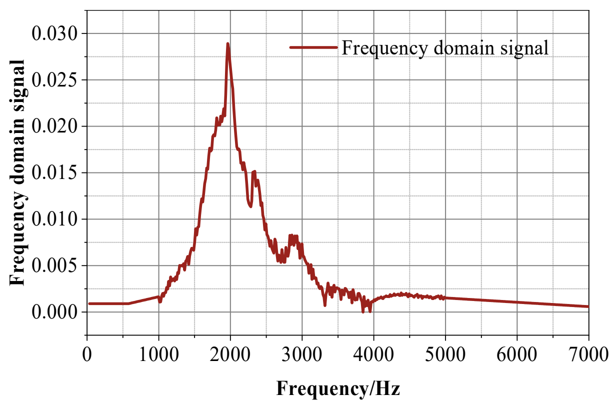


Figure 6: The frequency domain curve of a measuring signal of 3# point

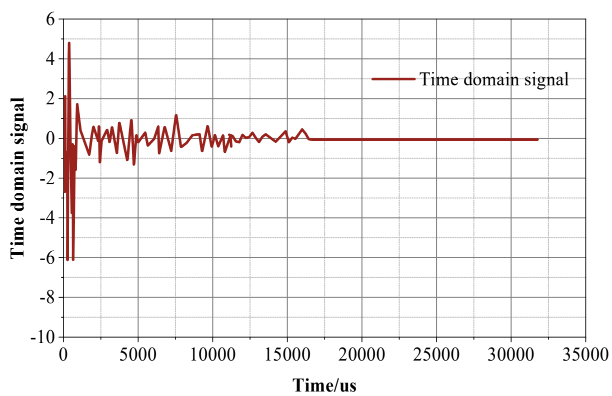


Figure 7: The time domain curve of a measuring signal of 8# point

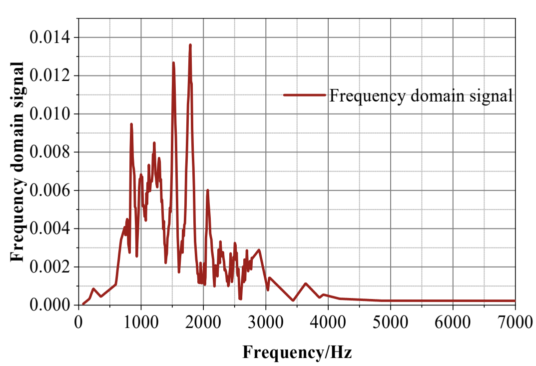


Figure 8: The frequency domain curve of a measuring signal of 8# point

V. Conclusion

With the rapid development of the construction industry and cities, people put forward higher requirements for the construction and quality supervision of human defense projects. In this study, BIM technology is used to build a quality monitoring system for human defense projects, and the non-contact impact echo acoustic-frequency method is combined with the YOLOv2-Tiny algorithm to construct a quality inspection model for human defense projects. The BIM technology and impact echo acoustic frequency method are integrated to monitor the quality and health of the human defense project.

(1) The use of migration learning can still achieve good training results with extremely limited training samples, and the overall prediction accuracy is over 96%. The identified defect types and locations are very accurate, and the generalization ability of the model is also tested. Therefore, the quality detection judgment technique based on the IAE method and YOLOv2-Tiny algorithm is not a highly efficient health monitoring method for human defense projects.

(2) The BIM-based quality monitoring system for human defense engineering is utilized to manage the construction and design works of the case, which verifies the application value of BIM technology for use in the health monitoring of human defense engineering. In this paper, the detection error of the impact echo acoustic frequency method for steel pipe concrete components is less than 2.81%, showing a more accurate identification effect, and it is feasible to utilize migration learning and the impact echo acoustic frequency method for the health monitoring of the human defense project.

With the gradual increase in the scale of construction of human defense projects, the use of BIM technology and non-contact impact echo acoustic frequency method to enhance the productivity of the construction industry, improve the level of refinement of the construction industry, reduce the waste of resources in the construction process, and to create a resource-intensive society is of great significance.

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