Research on non-destructive testing technology of rock bolt grouting compactness based on ultrasonic guided wave and deep learning

Abstract: In this paper, a new Deep Trans-Fourier Transform (DT-FT) method is proposed, which combines deep Q network (DQN), fast Fourier transform (FFT) and Transformer. It is applied to the non-destructive testing technology of rock bolt grouting based on ultrasonic guided wave and deep learning. There are many limitations in the traditional method of testing the density of bolt grouting, such as low accuracy and complicated operation. DT-FT method uses FFT to convert ultrasonic guided wave signals in frequency domain, and extracts rich frequency features. DQN is used to optimize the decision-making process and select the best feature combination to improve the detection accuracy. At the same time, Transformer is introduced to enhance the model's ability to process long sequence data and improve the accuracy and real-time detection. In the experimental part, we compared DT-FT with traditional detection techniques. The experimental results show that the DT-FT method has the advantages of high detection accuracy and strong adaptability, which fully verifies the feasibility and effectiveness of DT-FT non-destructive testing technology in the density of bolt grouting.

Keywords: Deep learning, detection techniques, fast fourier transform.

I. INTRODUCTION

In the safety evaluation and maintenance of engineering structure, it is a crucial task to test the density of bolt grouting. It is directly related to the stability and durability of the structure, and is a key element to ensure the quality and safety of the project. However, there are many limitations in the traditional methods of testing the density of bolt grouting, such as drilling coring method and sonic detection method. These methods are not only complicated and time-consuming, but also difficult to meet the high standards of efficiency and accuracy of modern engineering due to the limitation of human factors and instrument accuracy. Therefore, exploring an efficient, accurate and non-destructive testing technology for the density of bolt grouting has become an important issue to be solved urgently in the current engineering field.

In recent years, with the rapid development of ultrasonic guided wave technology, its application in the field of nondestructive testing is increasingly extensive. As a kind of mechanical wave propagating in solid medium, ultrasonic guided wave has the characteristics of long propagation distance, small attenuation, sensitive to medium defects, etc., and can effectively reflect the physical state and structural characteristics of materials. In the test of grouting density of bolt, ultrasonic guided wave technology can indirectly evaluate grouting density by analyzing wave propagation characteristics, such as wave speed, waveform, amplitude, etc. However, relying only on the traditional ultrasonic guided wave analysis technology, it is often difficult to extract useful feature information from complex signals, which limits its detection accuracy and reliability.

In order to overcome this problem, deep learning technology came into being. As a branch of machine learning, deep learning [1-3] can automatically extract high-level feature information from original data by building a deep neural network model, providing new ideas and methods for nondestructive testing. In particular, models such as Deep Q Networks (DQN) and Transformer demonstrate superior capabilities in processing complex data, optimizing decisions, and sequence modeling. By simulating the human learning process, DQN can find the optimal strategy in the complex decision environment, which provides a strong support for the feature selection and optimization of ultrasonic guided wave signals. With its powerful sequence processing capability, Transformer model can efficiently process long sequence data, providing a new means for fine analysis and pattern recognition of ultrasonic guided wave signals.

Based on the above background, a new Deep Trans-Fourier Transform (DT-FT) method is proposed in this paper, which aims to combine deep Q network (DQN) [4], Fast Fourier Transform (FFT) [5,6] and Transformer. Study on non-destructive testing technology of grouting density of bolt based on ultrasonic guided wave. Firstly, FFT is used to convert ultrasonic guided wave signals in frequency domain, and rich frequency features are extracted. As an efficient algorithm, FFT can convert the time domain signal into the frequency domain signal and reveal the distribution characteristics of the signal in the frequency domain. Through FFT processing, we can extract frequency components closely related to grout compactness from ultrasonic guided wave signals, which provides powerful data support for subsequent feature extraction and pattern recognition.

In the aspect of feature extraction, this paper introduces deep Q network (DQN) for optimization decision. By simulating the human learning process, DQN can automatically select the best feature combination in the complex feature space to improve the accuracy and robustness of detection. In the DT-FT method, the DQN model receives the frequency features extracted by FFT as input, and gradually optimizes its internal parameters and decision-making strategies through training and learning, so as to achieve accurate evaluation of grouting compactness.

In addition, in order to further enhance the model's ability to process long series data, this paper also introduces Transformer model. Transformer model [7], with its powerful sequence modeling capability, can efficiently process long sequence data in ultrasonic guided wave signals and extract deeper feature information. With the introduction of Transformer model, the DT-FT method can better deal with complex and variable ultrasonic guided wave signals and improve the accuracy and real-time detection.

To sum up, the Deep Trans-Fourier Transform (DT-FT) method proposed in this paper combines Deep Q network (DQN), Fast Fourier Transform (FFT) and Transformer to provide a new solution for the non-destructive testing of rock grouting compactness. This method not only overcomes the limitations of traditional testing methods, improves the accuracy and efficiency of testing, but also opens up a new direction for the development and application of nondestructive testing technology. Through theoretical analysis and experimental verification, this paper is expected to provide new ideas and methods for the research and application of non-destructive testing technology for the density of bolt grouting, and provide more efficient, accurate and simple testing means for engineering practice. In the future, we will further optimize the DT-FT method, and explore its scalability and practicality in more engineering inspection application scenarios, and provide new ideas and technical support for realizing more intelligent engineering inspection services.

II. RELATED WORK

As an indispensable supporting structure element in geotechnical engineering, anchor bolt is widely used in a series of geological engineering projects such as underground excavation and slope stabilization. The axial force of bolt, as the core index to measure its stability and safety, plays a vital role in ensuring the safe operation of the project. Bolt support technology occupies a core position in the fields of rock mass stability, tunnel driving and underground space development, etc. Through continuous monitoring means, it can keenly capture the initial signal of surrounding rock instability and effectively prevent the occurrence of disasters such as roof fall.

Ana Ivanovic et al. [8] conducted an in-depth study on the frequency response characteristics of bolt under load. They found that the influence of load on the frequency of bolt was not evenly distributed, but showed a non-uniform characteristic that the low-order frequency was more affected and the high-order frequency was less affected. Based on this information, they constructed a centralized parameter model in order to delve deeper into the mechanism through which external excitation loads influence the dynamic properties of the anchoring system.

In his work [9], Li comprehensively analyzed the factors influencing the contact stress between the support plate and the surrounding rock through a seamless integration of theoretical analysis and numerical simulation. The research results show that the higher the integrity of surrounding rock, the vibration frequency of anchoring system components will increase accordingly, which provides a scientific basis for the optimization of bolt support design.

In the field of non-destructive testing of bolt preload state, scholars at home and abroad have also achieved remarkable research results. They mainly use the nonlinear vibration response of the bolt to detect its axial force state. Xu W[10] pointed out that the loss of bolt preload would not only lead to the failure of fasteners, but also reduce the stiffness of the entire structure. Caccese V[11] used frequency-domain analysis to study the change of bolt preload in a square composite plate stimulated by a piezoelectric driver, and successfully detected loose bolts.

Brns[12] proposed an innovative detection method based on the nonlinear vibration response of bolts to detect their axial force. The experimental results show that there is an obvious correlation between the transient vibration of bolt and its tension, which provides a possibility for real-time monitoring of bolt tension.

In addition, Chen[13] also proposed a prediction model of the change of anchor cable and rock prestress based on the assumption of equal strain. The validity of this model is proved by the actual case data, which provides a solid theoretical basis for the safe operation and management of prestressed anchor cable engineering.

III. Fast Fourier Transform

Fast Fourier transform (FFT) is an efficient and fast calculation method of discrete Fourier transform (DFT). The formula of discrete Fourier transform is shown below.

$$X[k]=\sum_{n=0}^{N-1}x[n]e^{-\mathrm{j}k2Nn} \qquad (1)$$

Where x[n] represents a finite length sequence, $e^{-\mathrm{jk2Nn}}$ can also be written as the rotation factor W_N^{kn}, using the fast Fourier transform algorithm to simplify the calculation process of discrete Fourier transform algorithm is carried out by the idea of divide and divide algorithm and some characteristics of the rotation factor W_N^{kn}.

$$X[k]=\sum_{m=0}^{2N-1}x[2m]W_N^{k2m}+\sum_{m=0}^{2N-1}x[2m+1]W_N^{k(2m+1)} \qquad (2)$$

Equation (2) is converted according to the scaling of the rotation factor to get equation (3) as shown below.

$$X[k]=F_{\mathrm{even}}[k]*W_N^kF_{odd}[k] \qquad (3)$$

Where, $F_{\mathrm{even}}[k]$ represents the result after $f_{\mathrm{even}}[n]$ is input discrete Fourier transform, and $F_{\mathrm{odd}}[k]$ represents the result after $f_{\mathrm{odd}}[n]$ is input discrete Fourier transform. Equation (4) is obtained by transforming equation (3) according to the periodicity of the rotation factor.

$$X[k+\frac{N}{2}]=F_{\mathrm{even}}[k]*W_N^kF_{\mathrm{odd}}[k] \qquad (4)$$

By analyzing the formula mentioned above, it becomes clear that the result of the discrete Fourier transform for an M-point sequence can be obtained by separately calculating the discrete Fourier transforms of its odd-indexed and even-indexed elements. A visual representation of this particular process is provided in Figure 1.

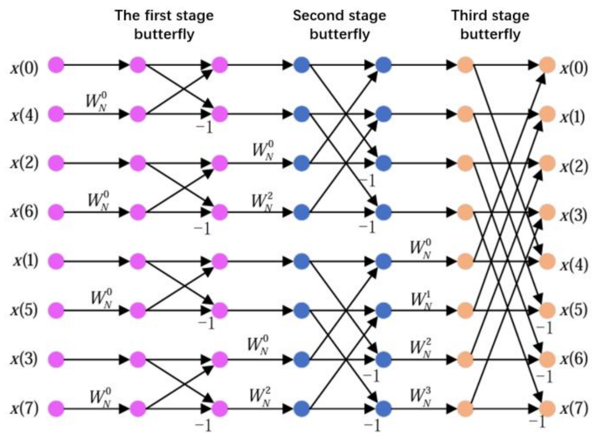

Fig. 1. Fast Fourier transform example

IV. DEEP Q-NETWORK

The core idea of deep Q network (DQN) is to use neural network to approximate Q function, namely state-action value function Q(s, a). This function represents the expected return of taking a particular action in a given state. Through continuous interaction with the environment and constantly updating the Q value, the DQN model can gradually learn the optimal behavior strategy, as shown in Figure 2.

We set S as a state space, where each state s ∈ S represents a unique configuration or situation of the network. At the same time, A is set as an action space, where each action a ∈ A corresponds to a possible detection operation, such as allow, prevent, further examine, etc. In addition, R acts as a reward function, which defines the immediate reward r received after performing an action.

To approximate Q function, we introduce a neural network Q(s, a; θ), where θ represents the parameters of the network. In order to break the correlation between the data and improve the stability of the training, we use an experience playback buffer D to store past interaction experiences (s, a, r, s').

Further, we define a loss function L(θ) to quantify the difference between the predicted Q value and the target Q value.

$$L(\theta) = E_{(s,a,r,s')\sim D}\left[\left(y_i - Q(s,a;\theta)\right)^2\right] \qquad (5)$$

Where y_i is the target Q value, which is calculated as follows:

$$y_i = r + \gamma \max Q(s',a';\theta^*) \qquad (6)$$

Where γ is the discount factor and θ* is the target network parameter.

By optimizing the algorithm to minimize the loss function, update the network parameter θ :

$$\theta \leftarrow \theta - \alpha \nabla_\theta L(\theta) \qquad (7)$$

Where α is the learning rate.

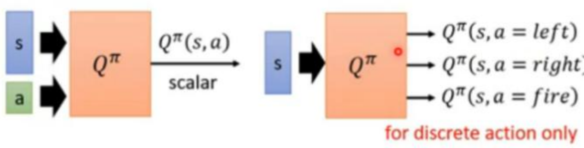

Fig. 2. DQN diagram

V. TRANSFORMER

In this paper, the Transformer model is selected as a powerful feature extraction tool, and its core highlight is its unique self-attention mechanism. This mechanism can capture the long distance dependencies that are common in sequence data in parallel and efficiently, so it shows excellent ability and great potential in processing sequence data. With its outstanding performance and high scalability, Transformer has become a shining pearl in the field of serial data processing.

The Transformer model follows a classic encoder-decoder structure, where the encoder and decoder are stacked with multiple layers of carefully constructed multi-head self-attention modules. This clever design makes Transformer a preferred solution for sequence-to-sequence tasks. Here are some of the core benefits of the Transformer model and its key components:

(1) Location coding: Since the self-attention mechanism itself does not consider the sequential characteristics of the input sequence, Transformer cleverly introduces location coding to accurately represent the specific position of words in the sequence. This innovative design allows the model to accurately distinguish between words at different locations, which in turn makes it more efficient in processing sequence information.

(2) The self-attention mechanism, which is integrated within the Transformer architecture, grants the model the ability to assign varying levels of attention to different positional information during the processing of input sequences. This mechanism dynamically adjusts the weights assigned to information at various positions according to actual needs, allowing the model to precisely capture long-range dependencies. Specifically, the self-attention mechanism generates outputs in the form of vectors by mapping a query (Q) onto a set of key-value (K-V) pairs. Both the query (Q), keys (K), and values (V) are represented as vectors. The computation process is carried out as follows:

$$Attention(Q,K,V)=Softmax\left(\frac{QK^T}{\sqrt{D_K}}\right)V \quad (8)$$

In this framework, the Softmax function plays a crucial role in ensuring that the output probability distribution is normalized, with its sum precisely equal to 1, thereby maintaining the integrity of the probability distribution. Additionally, the strategy of scaling the dot product by combining the query vector (Q) with the key vector (K) and dividing by √D effectively addresses the issue of gradient vanishing, significantly enhancing the stability of model training. The self-attention mechanism has been innovatively extended to a multi-head attention mechanism, which comprises multiple attention heads. This enables the model to simultaneously focus on different parts of the input sequence, allowing it to capture and integrate a wider range of representational information more efficiently, thereby substantially boosting its representational capacity.

(3) Feedforward neural network module: The feedforward neural network layer is cleverly embedded in the encoder and decoder of Transformer model. This module is responsible for deep nonlinear transformation of the eigenvector at each position. By introducing activation function and complex matrix operation, it greatly enriches the expressiveness and generalization performance of the model. The specific calculation process covers multiple levels of matrix multiplication and activation operations, aiming at deep mining of hidden rules and features in the data.

$$\mathrm{FFN(x)=max(0,xW_1+b_1)W_2+b_2} \quad (9)$$

Where x represents the feature vector of the current layer, and w_1 and w_2 represent the weight matrix of the two linear transformations, respectively. b_1 and b_2 represent the bias vectors of two linear transformations, respectively.

(4) Residual connection and normalization module: Each sub-layer in the model includes residual connection and layer normalization, which helps to improve the training stability and convergence speed of the model. The calculation process of residual join and layer normalization is shown below.

$$H'=LayerNorm\left(SelfAttention(X)+\alpha_{tj}\right) \quad (10)$$

Where H' and X are the output of the previous layer, LayerNorm is the layer normalization operation, and SelfAttention is the self-attention mechanism operation.

VI. DEEP TRANS- FOURIER TRANSFORM

In this paper, a brand new NDT technology, Deep Trans-Fourier Transform (DT-FT), is proposed, which cleverly combines three technologies, Deep Q network (DQN), Fast Fourier Transform (FFT) and Transformer, aiming to break through the limitations of traditional testing technologies. It provides a new path for non-destructive testing of the density of bolt grouting, and its working principle is shown in Figure 3.

One of the core methods of DT-FT is to use FFT to convert ultrasonic guided wave signals in frequency domain. As a kind of mechanical wave propagating in solid medium, the propagation characteristics of ultrasonic guided wave are closely related to the physical state and structural characteristics of the medium. The frequency component of ultrasonic guided wave signal can directly reflect the internal structure and compactness of grouting material in the test of grouting density of bolt. As a fast and efficient algorithm, FFT can convert the time domain signal into the frequency domain signal and reveal the distribution characteristics of the signal in the frequency domain. Through FFT processing, we can extract the frequency features closely related to grouting compactness from the complex ultrasonic guided wave signal, which provides powerful data support for the subsequent feature analysis and pattern recognition.

After extracting rich frequency features, how to effectively use these features to make decisions and judgments becomes the key to improve the detection accuracy. Therefore, the DT-FT method introduces deep Q network (DQN) to optimize the feature combination. DQN is a reinforcement learning algorithm based on deep learning, which can automatically select the best feature combination in the complex feature space to maximize the detection accuracy by simulating the human learning process. In the DT-FT method, the DQN model receives the frequency feature extracted by FFT as input, and gradually finds the feature combination that can best reflect the change of the density of the bolt grouting through continuous learning and optimization. This process not only improves the accuracy of the detection, but also enhances the robustness and adaptability of the model, enabling it to maintain stable detection performance under different environments and conditions.

In nondestructive testing of grouting density of bolt, ultrasonic guided wave signal often contains a lot of time series data. These data contain a wealth of structural information, but the traditional processing methods are often difficult to capture and use these information effectively. To solve this problem, the DT-FT approach introduces the Transformer model. Transformer is a deep learning model based on a self-attention mechanism that can efficiently process long sequences of data and capture global dependencies in the data. In the DT-FT method, Transformer model is used for fine analysis and pattern recognition of ultrasonic guided wave signals. By introducing Transformer, the DT-FT method can more accurately capture small changes in the signal, further improving the accuracy and real-time detection.

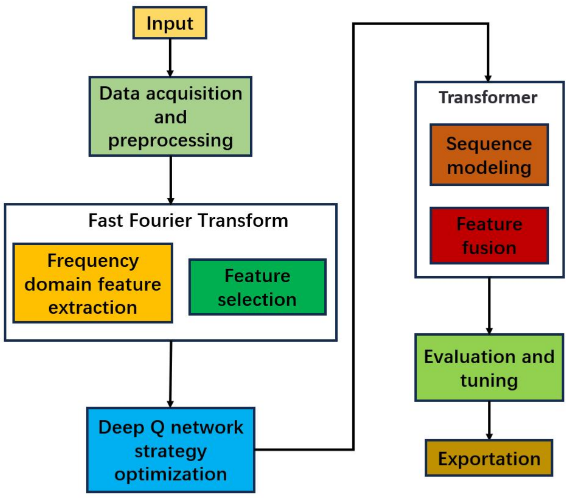

Fig. 3. DT-FT workflow

VII. EXPERIMENT

A. *Experimental environment*

This study integrates multi-source data from laboratory tests, field acquisition, historical archives, and simulation, covering time domain signals, such as time-voltage waveforms and spectral features captured directly by ultrasonic guided wave sensors, frequency distribution maps obtained by fast Fourier transform, image data, such as structural images from CT scans, and label information. Grouting density grade marked by professional engineers. In order to ensure data quality and applicability, we carry out detailed data pre-processing: in terms of cleaning and de-noising, we remove duplicate values, process missing values, and reduce noise through advanced algorithms such as wavelet transform; In feature engineering, important variables are selected according to domain knowledge, and input features are optimized by constructing new features, such as wave velocity difference, band energy ratio, and normalization/standardization; In terms of data enhancement, use oversampling (SMOTE), undersampling, or generating countervailing networks (GANs) to create more diverse instances where the sample size is insufficient; In terms of segmentation and cross-validation, the data set is divided into training set, validation set and test set, and K-fold cross-validation strategy is used to evaluate the generalization ability of the model.

This high-end experimental environment is equipped with a top-of-the-line Intel Core i7 processor, up to 32GB of RAM memory, and a high-performance NVIDIA GeForce RTX 3080 graphics processor (GPU) to ensure powerful computing power. At the same time, it is equipped with 1TB high-speed solid state drive (SSD), which is designed for storing massive ultrasonic guided wave data and intermediate results in the processing process to meet the needs of large-scale data processing. In addition, the environment has a high-speed and stable Internet connection, which provides a strong guarantee for remote transmission of data and real-time analysis. In the hardware equipment, we are equipped with a complete ultrasonic guided wave detection system, including transmitter, receiver and advanced signal acquisition system, and also introduced strain gauge, accelerometer and other auxiliary sensors to accurately collect ultrasonic guided wave signals under different conditions, and real-time monitoring of the working state of the anchor.

In order to ensure the repeatability and accuracy of the experiment, we also set up a special experimental platform to simulate the environment of bolt grouting. On the software side, we have adopted the latest Windows 11 operating system and efficiently managed the Python 3.8 development environment through Anaconda. With PyTorch 1.x, a powerful deep learning framework, we can easily build and train deep learning models for intelligent analysis and processing of ultrasonic guided wave data. At the same time, the SciPy library in Python also provides us with a wealth of tools for the preprocessing and feature extraction of ultrasonic guided wave signals, which further improves the accuracy and efficiency of data analysis. In terms of training, the proposed algorithm adopts the optimizer of Adam training model, and the specific training parameters are shown in Table I.

TABLE I. EXPERIMENTAL PARAMETER

Argument	Value
Learning rate	0.01
Dropout	0.2
batch	128
Weight attenuation coefficient	0.05
Embedding	64

B. *Results and analysis*

To present the performance of the DT-FT model in a more intuitive manner, we conducted a comparison between the short-time Fourier transform (STFT) and the convolutional neural network (CNN).

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT METHODS

	MSE	RMSE	MAE
CNN	18.94	4.58	12.37
STFT	18.24	3.64	12.28
DT-FT	15.67	2.56	11.68

As shown in Table II, we compare the performance of the three key performance indicators of mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) by different detection methods in detail. From the data analysis, DT-FT method has excellent performance in all three indexes: its MSE is the lowest, only 15.67; RMSE also reaches the minimum value of 2.56, which shows better processing ability for large errors. At the same time, MAE is 11.68, indicating that the average deviation between the predicted value and the actual value is minimal. In contrast, STFT method is superior to the traditional CNN method in various indexes, but its overall performance is still inferior to DT-FT.

To sum up, the excellent performance of DT-FT method in MSE, RMSE and MAE three key indicators proves its superiority in the task of non-destructive testing of rock grouting compactness. The DT-FT method can provide more accurate and reliable test results from the mean squared error, the sensitivity to larger errors, and the mean deviation. Therefore, in applications requiring high-precision detection and low error, such as ensuring the safety and stability of engineering structures, DT-FT is undoubtedly the best choice. Although the STFT method also shows good performance in some aspects, its overall performance still lags behind that of the DT-FT, while the CNN method performs least well in these three indicators, especially in dealing with large errors and the mean squared error, which makes it not the first choice for detection tasks requiring high reliability and accuracy.

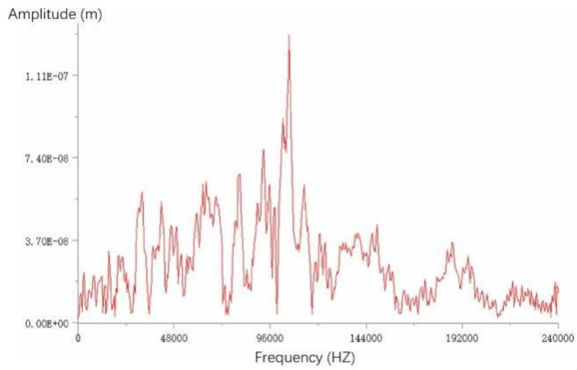

Fig. 4. The DF-FT detects waveform signals in the frequency domain

The signal amplitude variation of NDT technology is shown in Figure 4. The abscissa represents the frequency (from 0 to 240,000 Hz), while the ordinate represents the amplitude, in meters (m), ranging from 0 to about 1.11E-07 m. The signal amplitude fluctuates significantly over the entire frequency range, especially reaching a maximum peak at approximately 120,000 Hz, over 1.11E-07 m. This frequency may be caused by a specific resonance frequency or reflection characteristic in the bolt grouting material, reflecting the main structural characteristics inside the material. In addition, significant amplitude changes were observed at other frequency points, and although these amplitude values are relatively small, they may reveal different structural features or potential defects within the material. There are also some random fluctuations in the chart, which are caused by noise and other interfering factors.

In summary, it can be concluded from the figure above that 120,000 Hz is one of the main frequency components of the signal, corresponding to specific physical properties in the material, such as resonance frequency or reflection properties. In addition to this primary frequency, other frequency components also show some amplitude fluctuations, and these smaller amplitude changes help to understand more subtle structural differences or defects within the material. The random fluctuations in the chart suggest that there may be noise and other interfering factors in the actual detection process, which poses a challenge for signal analysis. Understanding these frequency components and interference characteristics is critical to optimizing the detection model, helping to improve detection accuracy and reliability.

VIII. SUM UP

In this paper, an innovative method called Deep Trans-Fourier Transform (DT-FT) is proposed. This method skillfully integrates Deep Q network (DQN), Fast Fourier transform (FFT) and Transformer, aiming to overcome the limitations of the traditional detection technology in the detection accuracy and operation complexity. Specifically, the DT-FT method first uses FFT to convert ultrasonic guided wave signals in the frequency domain, so as to accurately extract rich frequency features and provide key information for subsequent detection. Then, by introducing DQN, the method can intelligently optimize the decision-making process and automatically select the best feature combination to further improve the detection accuracy. At the same time, the addition of Transformer greatly enhances the model's ability to process long series data, ensuring the accuracy and real-time detection. In order to verify the feasibility and effectiveness of DT-FT method, detailed experimental comparison is carried out in this paper, and the results show that compared with traditional detection techniques, DT-FT method shows significant advantages in detection accuracy and other aspects. This innovative achievement not only brings a new breakthrough for the non-destructive testing technology of the density of bolt grouting, but also provides a strong technical support for the accurate detection of the density of bolt grouting in engineering practice. In the future, we will continue to deepen relevant research and promote the widespread application of DT-FT method in practical engineering.

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