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A review of the Research on Tunnel Lining Voiding Detection Based on Acoustic Vibration Method

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Abstract: In the study of nondestructive testing technology for tunnel lining voiding detection, the traditional nondestructive testing technology has many drawbacks such as poor detection accuracy, high subjectivity, and easy to be interfered with, etc., and the combination of acoustic vibration method and deep learning technology has the problems of uneven distribution of the data set, poor interpretability, and other problems that are difficult to be applied to industrial applications, which summarizes the current acoustic vibration testing technology and its application to the study of tunnel lining voiding. Firstly, the non-destructive testing techniques used in the current tunnel lining voiding detection research are sorted out, and then a variety of tunnel lining voiding detection research methods based on acoustic vibration method with potential applications in the industrial field are analyzed, followed by an overview of the current situation from the point of view of deep learning combined with the acoustic vibration method for the detection of tunnel lining voiding, and then the direction of the next step of the research is discussed and analyzed. The full paper is summarized, and future challenges are pointed out.

Keywords: Tunnel lining voiding detection, Acoustic vibration method, Deep learning.

1. Introduction

Tunnel is an engineering structure built underground, tunnel engineering in the construction of the project will often meet the complex geological conditions, the construction of technical difficulties and other issues, these issues make the tunnel project has complexity, hidden and uncertainty and other characteristics. The engineering characteristics of tunnel projects make it difficult to control the quality of the project, and the various defects inside the tunnel are difficult to be detected [1]. The internal defects of the structure continue to develop in the subsequent operation process, and may produce a series of diseases, such as lining deformation and cracks, structural water seepage, roadbed damage, etc., which seriously threaten the safety of traveling inside the tunnel, shorten the maintenance cycle and service life of the tunnel, and form a safety hazard and property loss [2]. Based on the above reasons, accurately identifying the location of the internal defects of tunnels is important for the stability of the tunnel structure, safety of traveling inside the tunnel as well as the economy of tunnel maintenance and reinforcement are crucial [3].

The lining is a concrete structure built on the surface of the tunnel body, which is a major load-bearing structure of the tunnel. The strength and stability of the lining structure affects the safety and durability of the tunnel. Due to the hidden nature of tunnel construction and the complexity of tunnel construction, many quality problems and accidents still occur in the construction and operation of tunnel projects. The lining is subject to most of the loads transmitted by the surrounding rock, and its pouring quality is difficult to be guaranteed in the construction process [4]. Lining construction quality control is not in place, it will lead to lining structure to appear a variety of diseases, thus jeopardizing the safety of the structure, in the tunnel of all kinds of diseases, lining voiding is one of the most important factors affecting the safety of the tunnel structure, but also one of the highest morbidity rate of the disease, the cavity will make the lining uneven force, bearing capacity reduction and other issues. In addition, the existence of voids often indirectly leads to other diseases, such as lining cracking, tunnel water seepage and so on.

The traditional method of liner voiding detection is mainly the core drilling method. Because tunnels are engineering structures built underground, traditional inspection methods are difficult to detect the internal condition of the structure without damaging the lining structure due to technical limitations [5]. The core drilling method is to take core samples from the surface of the lining without affecting the lining's load bearing capacity and observe the internal condition of the lining through the core samples taken. The advantage of core drilling method is that it can visualize and accurately observe the engineering situation inside the lining, but the disadvantages of this kind of destructive testing method are very obvious, the efficiency of this method is low, the chance is big, the representativeness is poor, due to the need to drill holes inside the lining structure, it can't carry out large-scale comprehensive testing, and the repair work in the later stage is also more complicated. In addition, there is steel reinforcement inside the lining structure, and the location and depth of the drilling hole need to be determined when core drilling and sampling, in order to place the steel reinforcement that damages the internal structure [6]. In contrast to this kind of destructive testing methods, there are many non-destructive testing methods.

And according to the engineering characteristics of tunnel engineering, the modern lining voiding detection methods mainly use the non-destructive testing method. Commonly used non-destructive testing methods are mainly divided into several categories, such as geo-radar method, ultrasonic detection method, acoustic vibration method and so on.

Geo-radar method is to transmit electromagnetic pulse to the structure through the transmitting antenna on the surface of the north side of the structure, and the reflection of the electromagnetic wave in the structure of different media surface is transmitted back to the receiving antenna, and through the dielectric constant of the structure to be tested and the propagation speed of the electromagnetic wave in it, the depth of the different reflective media surface can be calculated, so as to detect all kinds of defects in the structure[7]. However, the geo-radar method has some limitations, that is, when water is present inside the structure, the variation of electromagnetic wave will increase. And the reinforcement inside the structure will also cause some difficulties in defect detection [8].

Ultrasonic inspection is one of the more common inspection methods, it is to talk about the piezoelectric transducer affixed to the surface of the structure to be tested, through the piezoelectric transducer voltage applied to the surface of the structure caused by the vibration of the structure to generate stress waves, through the analysis of the signals received by the receiving end of the structure to determine the internal situation [9]. The vibration frequency of ultrasonic testing is generally very high, usually above 20kHz. The higher the frequency of the signal, the higher the accuracy of the test, the attenuation will also become larger, resulting in ultrasonic detection method of detection distance is relatively short.

Acoustic vibration is also used to determine the internal condition of a structure by receiving stress waves propagating inside the structure [10]. The difference with ultrasonic testing is that ultrasonic testing generates high-frequency stress waves, whereas acoustic vibration testing has a lower frequency, usually a few hundred to a few thousand Hz, which is basically within the frequency range of the human ear [11]. Acoustic vibration method is generally the use of percussion hammer or steel ball and other objects to be tested objects between the markers for percussion, so as to produce low-frequency stress waves, acoustic vibration method has a lot of advantages such as easy to stimulate, easy to operate, detection of the depth of a large, so acoustic vibration is a powerful method of tunnel lining voiding detection.

2. Tunnel Sound Vibration Detection Technology

The most central idea in tunnel sound vibration detection technology is anomaly sound detection, Anomaly Sound Detection (ASD) is an important audio signal processing task aimed at detecting and identifying anomalies or anomalous events in audio signals. These anomalous sounds may include environmental noise, fault sounds, abnormal events, etc. Among these, automatic detection of mechanical and architectural faults is an important technology of the fourth industrial revolution, which involves artificial intelligence-based factory automation. Timely detection of anomalies by observing sounds is very useful for condition monitoring in industries. Fig. 1 shows an overview of the anomaly detection system.

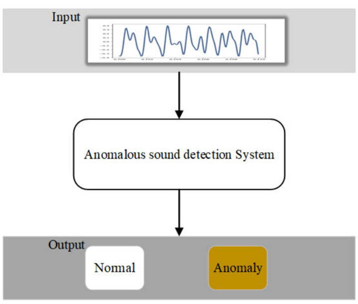

Figure 1. Abnormal sound detection process

Traditional abnormal sound detection methods are mainly based on signal processing and machine learning techniques, including frequency domain analysis, time domain analysis, feature extraction, and classifier design. Due to the specificity of abnormal sound detection, many downstream tasks suffer from inadequate abnormal sound datasets and insufficiently detailed patterns of abnormal sounds, so many abnormal sound detection algorithms are based on normal sound sample datasets for detection. The research on abnormal sound detection started relatively early, and the early methods through parameter estimation, to the reconstruction-based methods, and the later methods based on the support domain are all relatively classical work.

2.1. Abnormal sound detection based on parameter estimation

Since it is very difficult to obtain abnormal audio data in abnormal sound detection tasks, and general abnormal detection tasks use normal samples of this type of data for unsupervised learning, there is one of the simplest and most direct ways to perform abnormal sound detection, which can be parameterized by estimating the density model of the samples and setting the density threshold. One of the simplest estimation methods is to assume that the samples obey a unitary Gaussian distribution [12], as in equation (1):

$$p(x)=\frac{1}{\sqrt{2p\sigma}}\exp-\frac{(x-\mu)^2}{2\sigma^2} \tag{1}$$

Where μ is the mean of the normal data sample and σ is the variance, according to the 2σ and 3σ criteria of the Gaussian distribution:

$$\begin{aligned}&P(|x-\mu|<2\sigma)\\&P(|x-\mu|<3\sigma)\end{aligned} \tag{2}$$

Therefore, according to Equation (2), if the distance from the mean of a sample participating in a test is more than two or three times the variance, it can be decided that the test sample is uncertain, and it can be regarded as an anomalous sample. However, this model is too simple and for the data of one element, if you want to meet this model, you need to design good enough one element features to save enough features so that you can use this model to detect, and the design of this feature engineering is undoubtedly very complicated.

And since such one-dimensional features can be detected by obeying a one-dimensional Gaussian distribution, whereas if there is a multivariate data, abnormal sound detection can be carried out by assuming that all the data obeys a model with a multivariate Gaussian distribution [13], which is represented as in Eq(3):

$$p(x)=\frac{1}{\sqrt{(2\pi)^d\det(\Sigma)}}\exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)) \tag{3}$$

Where d is the dimension of the sample, μ is also the mean of the normal sample used for training, and ∑ is the covariance matrix of all the training samples. However, both of the above models for normal data are too simple to accommodate very complex data distributions, so later Sain [14] et al. used a different model for normal data based on a general data distribution, as in Eq (4):

$$p(x) = \frac{1}{\sqrt{(2\pi)^d}} \sum_{j=1}^{\gamma} \alpha_j \frac{1}{\sqrt{\det(\Sigma_j)}} \exp(-\frac{1}{2}(x-\mu_j)^T \Sigma_j^{-1}(x-\mu_j)) \quad (3)$$

Where d is still the dimension of the training sample, α_j is the mixing parameter, μ_j and $\sum_j$ are the mean as well as the covariance matrix of the jth component in the training sample, and γ is the number of mixing components, and finally, the maximization of expectation is used to optimize the parameters, and then according to the conditional probability of the test samples as well as the thresholds during the testing process, the detection of abnormal sound is carried out. However, the shortcoming of this method is that the mixture components are too data-dependent, and it is very difficult to select them with a small amount of data, which is itself a problem in the abnormal sound detection task.

2.2. Anomalous sound detection method based on support domain

The support domain-based abnormal sound detection method first assumes a descriptive shape for all normal data samples. Then, the correct classification rate of the training samples is ensured by minimizing the volume while minimizing the misdiagnosis probability of the abnormal samples, subject to a given empirical error. This approach aims to improve the performance of the anomalous sound detection classifier by shifting it upwards on the ROC curve, which in turn improves the detection performance. Classical approaches include single-class support vector machines, support vector data description, etc.

Support Vector Machine (SVM) is a very classical two-class classification method, which segregates the data samples used for training by finding a hyperplane with the largest classification interval [15]. In the field of anomalous sound detection, the original Support Vector Machine is no longer suitable for this task because the data set available for training is generally only one class of samples. Instead, Scholkrpf et al. proposed a model for anomaly detection based on a One-class SVM [16], which forms a data description. This one-class support vector machine has similar goals as the original support vector machine; however, this one-class support vector machine takes the origin as the only anomaly, and then looks for a hyperplane that separates the samples used for training and the origin with a maximum interval. Like the original support vector machine, there are soft-spaced and hard-spaced unclassified support vector machines, where the hard-spaced unclassified support vector machine requires that all training samples be on the positive half of this hyperplane, whereas the soft-spaced unclassified support vector machine does not have such a requirement but the soft-spaced support vector machine penalizes the data sample points that fall on the other half of the hyperplane based on the distance of that data sample's distance to the hyperplane, which can be solved by the problem of Eq (5) :

$$\begin{gathered} \min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i - b \\ s.t. \quad w \bullet x_i \geq b - \xi_i \\ \xi_i \geq 0, \forall i \end{gathered} \quad (5)$$

where w is the normal vector of the hyperplane and b is the intercept of the hyperplane to be searched. The empirical error and the interval $1/\| w \|$ between the hyperplane and the origin are compromised by a regularization factor C.

Support Vector Data Description (SVDD) is mainly used to solve the problem of possible looseness of data description in half-space in single-classification support vector machines, the method mainly focuses on finding a spherical description of the data, which surrounds as much as possible all the normal data training samples used for training, and at the same time minimizes the volume of this volume of the hypersphere [17]. With this idea, the Minimal Enclosing Ball (MEB) method uses a hard spacing approach, so the MEB method is susceptible to wild-value points and fails to find the smallest hypersphere [18]. In order to avoid the harm caused by such wild-value points, the support vector data description method uses soft spacing, which does not strictly require that the squared distance from the training samples to the center of the hypersphere is less than , but adopts the same penalization mechanism as the soft spacing classification in the unclassified support vector machine, which penalizes normal samples used for training for a squared distance greater than the squared distance from the center of the hypersphere, and introduces a relaxation variable to relax all training samples, making the original conceptual constraint that all data samples used for training should be inside the hypersphere less strict and allowing a small fraction of training samples to fall outside the sphere of the hypersphere. The optimization of the soft-spaced SVDD is shown in equation (6) ：

$$\begin{gathered} \min R^2 + C \sum_{i=1}^{n} \xi_i \\ s.t. \quad \| x_i - a \|^2 \leq R^2 + \xi_i, \quad \xi_i \geq 0, \forall i \end{gathered} \quad (6)$$

Here a denotes the center of the hypersphere and C is the regularization factor. By Lagrange multiplier method, the dyadic problem of the above problem can be obtained, and the above minimal-extremely large problem can be transformed into a convex quadratic programming problem and its dyadic $a = \sum_{i=1}^{n} \alpha_i x_i$ representation can lead to the sparsity of the sphere's center, which improves the testing performance of this model.

The Striped Data Description (Slab SVM) method is implemented by adding more constraints on top of the Single Classification Support Vector Machine (SCSVM) [19]. The Slab SVM proposed by Scholkopf et al. When they solved the hyperplane of the SCSVM, since the SCSVM uses a hyperplane to separate the normal data samples in the dataset from the far point, but the other side has no special constraints, so they built on this by using a hyperplane on the other side of the data to constrain the target as well, so that the data used for training will fall in a strip, and their problem can be described by Eq (7):

$$\begin{gathered} min \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) - b \\ \chi - \xi_i \leq w \cdot x_i - b \leq \chi^i + \xi_i^* \\ \xi_i \geq 0, \xi_i^* \geq 0 \end{gathered} \quad (7)$$

where χ and χ^* are fixed parameters used to determine the width of the entire strip, and ξ_i and ξ_i^* are slack variables. Through the description of the above problem, a strip space in the feature space in which the features of the training samples are located can be found, and then based on such a data description, after the test samples are modelled using this model, all the test data that are outside of the strip can be regarded as indeterminate, which can be judged as anomalous data samples.

2.3. Detection methods based on deep learning methods

Abnormal sound detection task based on deep learning is a kind of abnormal sound detection method that has been developed more rapidly in recent years, and this method usually uses deep neural networks to learn the representation of sound from a large amount of audio data, and in this way, to achieve the detection of abnormal sound. Due to the specificity of the abnormal sound detection task and the difficulty of acquiring abnormal sound datasets, most of the methods based on deep learning to implement abnormal sound detection systems are also based on unsupervised learning. Several common neural networks most commonly used in this abnormal sound detection task include full convolutional neural networks, auto-encoder (AE), and so on [20]. These neural networks are usually composed of an encoder and a decoder, where the encoder is used for feature extraction from the audio data and the decoder maps the extracted features to the original data space. Deep learning based anomalous sound detection schemes have high accuracy and robustness for a variety of anomalous sound detection tasks, but deep learning-based methods require a large amount of data for training to obtain a data representation of normal class audio data, and the interpretability of the model is relatively poor, which makes it difficult to interpret and correct the prediction results of the model [21-22].

In practice, anomalous sound detection tasks can be used in many fields, such as safety and security fields, health monitoring of equipment, environmental monitoring, medical diagnosis, and so on [23-24]. It can help people better understand the audio content, automate the process of abnormal sound detection, and achieve intelligent decision-making. However, abnormal sound detection still faces many challenges, such as audio data is easily affected by environmental noise, reverberation and other factors, low recognition rate of the algorithm, etc. It still requires continuous improvement and innovation of abnormal sound detection algorithms, and the combined use of different methods.

3. Discussion and Conclusion

Along with the rapid development of deep learning technology and the continuous demand in the field of tunnel engineering, the combination of acoustic vibration method and deep learning shows great potential in tunnel lining voiding detection. In the future, we can expect that the research in this field will show the following trends:

First, with the continuous progress of data collection technology and the increase of data volume, the acoustic vibration method combined with deep learning for tunnel lining voiding detection will pay more attention to the data-driven approach. By collecting more and more comprehensive tunnel lining acoustic vibration data and combining it with deep learning models for training as well as optimization, a more accurate and intelligent detection and assessment of tunnel lining voiding will be achieved.

Second, future research will be devoted to further optimization and innovation of deep learning models. More efficient and accurate deep learning models will be designed to address the pending problems and challenges in tunnel lining voiding detection. For example, by combining models such as convolutional neural network (CNN) and recurrent neural network (RNN), feature extraction and time series analysis of acoustic vibration data will be realized, so as to improve the sensitivity and accuracy of detection.

In addition, future research will pay more attention to the application and promotion of the method of combining the acoustic vibration method with deep learning technology in practical engineering. By combining with engineering practice, the deep learning model will be applied to the real-time monitoring, prediction and management of tunnel lining voiding to provide more reliable and intelligent support for the safe operation of tunnel projects.

Overall, combining the acoustic vibration method with deep learning in the field of tunnel lining voiding detection has a broad application prospect and development space. Future research will focus on three aspects, namely, data-driven, model optimization and engineering application, to promote the continuous innovation and progress in this field, and to make greater contributions to the safety management and development of tunnel engineering.

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