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Feature Extraction Algorithm of Cutter Head Pressure Signal based on Stack Auto-encoder

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Abstract: Tool system wear is one of the common faults affecting TBM system tunneling. In order to simulate the operation of the TBM tool system, judge its failure state, and locate the failure area of the hob, this paper designed the simulation experiment platform of the TBM tool system, and obtained the pressure signal of the tool plate when the tool plate is running through the experiment platform, and proposed the pressure feature extraction algorithm for the cutter head of the TBM tool system, so as to judge the failure state of the cutter head system and locate the failure area. Experimental results show that the cutter head pressure feature extraction and failure location algorithm proposed in this paper can effectively identify the cutter head region where the failure hob is located, and improve the efficiency of cutter head maintenance in the process of TBM tunneling.

Keywords: Tunnel Boring Machine (TBM); Cutting Tool System; Failure Determination.

1. Introduction

Full-section rock Tunnel Boring Machine (TBM) is a major technical equipment in urgent need of key breakthrough in our country, as shown in Figure 1.1. In tunnel excavation, due to its high tunneling speed and degree of automation, less damage to the surrounding environment, high comprehensive benefits, and more safety and reliability than traditional drilling and blasting method, it is widely used. TBM mainly includes tool system, cutter head system, hydraulic propulsion system, etc., and the tool system as the core component of the full section rock tunnel boring machine, its performance and reliability directly affect the engineering efficiency and construction cost.

In the process of TBM construction, the tool system is installed on the cutter head in the TBM hydraulic propulsion system thrust and hydraulic motor torque under the action of rock breaking, through the rock to produce a certain shear and extrusion to destroy the rock. The hob directly participates in the crushing of the rock. The working condition of the hob in the rock breaking is very complex, which is prone to severe wear and lead to failure, which seriously affects the efficiency of rock breaking. Therefore, it is necessary to carry out regular stop inspection to check whether the hob in the tool system fails. However, manual inspection of the failure hob takes too long, prolongs the construction time and seriously affects the construction efficiency[1].

It is a commonly used research method to determine whether the hob fails according to the pressure signal of the cutter head. Researchers used Wavelet transforms[3] and Neural Networks [2] to analyze tool fault prediction methods. Qin et al. [4] proposed a hybrid depth neural network (HDNN) based on equipment operating parameters and state parameters for accurate prediction of cutter head torque of shield boring machine. Zhou [5] et al. used artificial neural network, random forest regression and support vector regression to establish TBM PR model. In addition, Jin et al.[6] investigated the influence of rock properties and changes in TBM parameters on hob failure. A new hob wear model was developed by combining the Archard model with the TBM cutter head kinematics. Rostami et al.[7] modeled the cutter head system and analyzed the force on the rock broken by the hob and optimized the parameters of the cutter head system by consider different rock characteristics. These methods studied the wear mechanism of the TBM tool system, the force analysis of the hob rock breaking, etc., but there were few studies on the tool system failure diagnosis and failure region location.

In this paper, aiming at the common problem of hob failure in TBM construction, the depth characteristics of cutter head force signal in TBM excavation were extracted by SAE stack encoder (SAE), and support vector machine was used to determine the location of the failure hob, so as to improve the efficiency of cutter head fault maintenance in excavation process.

Fig 1. Full-section tunnel boring machine

2. Feature Extraction Algorithm of Cutter Head Vibration Signal

Stacked Autoencoder (SAE) is a deep learning method, whose basic idea is to extract higher-order features of data layer by layer through multiple autoencoders. The network architecture proposed in this paper is shown in the figure. Wherein, the input signal matrix of the network is $X = [x_i]_{i=1}^{C}$, $X \in \mathbb{R}^{C\times T}$. Similarly, the class tag vector of the hybrid network is $Y \in \mathbb{R}^{C\times 1}$. The encoder of SAE can be expressed as:

$$h = \sigma(Wx + b)$$

Where, x is the input sample, W is the weight matrix, b is the bias vector, σ is the activation function, and h is the hidden layer output.

The decoder can be expressed as:

$$\tilde{X} = \sigma(W'h + b')$$

Where y is the hidden layer output, W' is the weight matrix, b' is the bias vector, σ is the activation function, and $\tilde{X}$ is the reconstruction layer output.

For self-coding networks, in order to find the optimal one of W, b, W', b', the following formula can be minimized to evaluate the weight matrix and bias of the hidden layer:

$$J(W,b) = \sum_{i=1}^{Tr} \| \tilde{x}_i - x_i \|_2^2 + \frac{\lambda}{2} \| W \|_2^2 + \alpha \sum_{j=1}^{\theta_{Tr}} K L\left(\frac{\rho}{\tilde{\rho}_j}\right)$$

Where, KL $(\frac{\rho}{\tilde{\rho}_j})$ is the Kullback-Leibler (KL) divergence between, $\tilde{\rho}_j$ the average activation (averaged over the training set) of hidden unit j, and desired activations ρ, λ is the regularization term. In the actual network, the cross-entropy loss function $\mathcal{L}_{ce}$ is used to optimize the reconstruction error of SAE. The formula is as follows:

$$\mathcal{L}_{ce} = x\log(\tilde{x}) + (1-x)\log(1-\tilde{x})$$

Consider using radial basis function (RBF) SVM classifier to classify feature vectors. The classifier can be represented by the following classification function:

$$f(x) = sgn(\theta x + c)$$

Where, θ is the weight vector of the classification plane, c is the bias vector of the classification plane, Gaussian radial basis kernel function $K(x, x_i)$ is introduced, and the final classification function is expressed as:

$$f(x) = sgn(\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + c)$$

3. Experimental and Results

3.1. Experimental and Datasets

The tool system failure diagnosis and failure area location are performed using the experimental data of the hob simulation test platform, as shown in Figure 2. The experimental platform mainly includes the experimental table, the propulsion mechanism, the load simulation system and the rotating application module. The experimental table is welded by 10a and 12a channel steel, and horizontal steel plates are welded on the channel steel frame. The propulsion mechanism consists of six propulsion hydraulic cylinders, and the rodless cavity of each cylinder is respectively provided with a pressure sensor, which can adjust the thrust size of the propulsion cylinder by adjusting the relief valve. The propulsive mechanism comprises a propulsive support plate and 6 articulated structures. The load simulation device is connected with the propulsive mechanism through a walking support plate. The load simulation device includes 8 adjustable spring dampers, articulated mechanism, support mechanism, flat plain bearing and rotating disc.

Experiment by stratified sampling selected tool system failure and tool system four zones failure of 5 types of data, each type of data were intercepted 600 trials, a total of 3000 trials, as the data set of this experiment.

Fig 2. Actual lab bench construction

3.2. Results

In order to accurately identify the cutter head region where the failure hob is located, the stack auto-encoder (SAE) is used to extract the pressure signals in different regions of the cutter head, and the depth characteristics of the multi-channel pressure signals are extracted. Then, according to the stress characteristics of the cutter head, support vector machine (SVM) was used to identify the cutter head region where the failure hob was located.

According to the experimental data collected by the hob simulation test platform, we identified five types of pressure signals: no hob failure, upper partition failure, lower partition failure, left partition failure and right partition failure. The experimental results are shown in Table 1.

As can be seen from the table, the recognition accuracy rate of hob without failure is higher than that of failure. This is because when hob is running normally, the pressure signal received by each area of cutter head is uniform, which is quite different from that when hob failure occurs. In addition, the recognition accuracy of upper and lower partition failure is higher than that of left and right partition. Among them, the lower partition hob failure identification efficiency is the best.

Table 1. Comparison of model results

Tool system failure area	Accuracy of SAE-SVM model
No failure occurred	100%
Upper partition failure	83.3%
Lower partition failure	93.3%
Left partition failure	76.7%
Right partition failure	75%

4. Summary

In this paper, the tool system of TBM is taken as the research object. In order to improve the maintenance efficiency of the tool system, the algorithm of cutter head pressure feature extraction and failure region location is proposed. Using SAE algorithm to extract the depth characteristics of cutter head pressure signal, and using SVM to judge whether the tool system failure occurred under the characteristics, and locate the failure problem cutter head region, has important guiding significance for the operation and maintenance of tool system.

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