A Signal Filtering Method for Magnetic Flux Leakage Detection of Rail Surface Defects Based on Minimum Entropy Deconvolution

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ABSTRACT

Magnetic flux leakage (MFL) detection of rail surface defects is an important research field for railway traffic safety. Due to factors such as magnetization and material, it can generate background noise and reduce detection accuracy. To improve the detection signal strength and enhance the detection rate of more minor defects, a signal filtering method based on minimum entropy deconvolution is proposed to denoise. By using the objective function method, the optimal inverse filter parameters are calculated, which are applied to the filtering detection of MFL signals of the rail surface. The detection results show that the peak-to-peak ratio of the defect signal and noise signal detected by this algorithm is 2.01, which is about 1.5 times that of the wavelet transform method and median filtering method. The defect signal is significantly enhanced, and the detection rate of minor defects on the rail surface can be effectively improved.

KEYWORDS

Defect, Magnetic Flux Leakage Detection, Minimum Entropy Deconvolution, Signal Filtering

INTRODUCTION

Nowadays, the railway is an essential mode of transportation for people. Ensuring the safe operation of the railway network is of great significance. As an essential component of railway transportation, steel rails play an important role. When a train runs on the steel rail, the pressure of the wheels and the long-term effect of the external environment on the steel rail will cause defects in the surface of

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the rail, such as rail surface wear, crushing, and peeling. The development of defects may ultimately lead to significant safety accidents, such as train derailment and overturning, causing significant casualties and substantial property losses (Jia et al., 2020). Therefore, nondestructive testing (NDT) of steel rails is significant for railway traffic safety.

NDT is a method of testing the integrity of an object based on physical and chemical principles. It uses testing equipment to detect the tested object in all directions effectively. With the rapid development of NDT technology, it has been applied in fields such as aviation, construction, and special equipment. At present, NDT technology for steel rails includes Ultrasonic testing, eddy current testing, and MFL testing. MFL detection technology is used widely for NDT of surface defects in ferromagnetic components, such as wire, piping, and rail, owing to its simple sensor structure, high detection sensitivity, and ability to achieve noncontact detection (Chandran et al., 2019). However, the collected MFL signals are mixed with various noises, such as system noise, spatial magnetic field noise, noise generated by velocity effects, magnetization, and material noise (Jia et al., 2022; Jik et al., 2021; Bevan et al., 2022). Especially when the rail defect detection vehicle is conducting high-speed inspections on site, on one hand, more complex electromagnetic effects are highlighted, which are reflected in the measured signal as stronger background noise. On the other hand, the vibration of the probe's mechanical structure causes interference in lifting. For more minor surface defects of steel rails, such as scratches and cracks with shallow depth and small surface area, the MFL detection signal is weak and difficult to identify, leading to missed detection. Therefore, it is essential to preprocess the measured signal and enhance the defect signal before extracting the features of the MFL signal, identifying and quantifying the surface defects.

Scholars have researched the preprocessing of MFL signals. For example, Dong et al. (2022) used the adaptive shift average method to reduce the noise of the wire rope defect signal and also used the quantum particle swarm optimization algorithm to optimize the window width of the shift average method to maximize the signal-to-noise ratio. Zhang et al. (2019) proposed a multilevel filtering method combining wavelet denoising and median filtering to improve the accuracy of MFL detection. Cao et al. (2019) combined data layer fusion, feature layer fusion, and decision layer fusion based on wavelet multiscale transformation and decomposition to improve the accuracy of MFL edge detection. To improve the accuracy of quantitative analysis, correction algorithms, weighted gradient algorithms, and decoupling algorithms have also been used in the preprocessing of MFL signals (Zhang et al., 2021). The physics-inspired metaheuristic algorithm proposed by Priyadarshini et al. (2023) for K-nearest neighbor (KNN) analysis feature selection uses six physics-inspired metaphorical algorithms for feature selection. The integrated balance optimizer can apply to noise signal extraction, outperforming other algorithms in terms of average fitness, average accuracy, and average quantity. Ganesh et al. (2023) further proposed a feature selection packaging system based on KNN, which uses the iterative improvement ability of weighted superposition attraction further to improve the feature selection performance of noisy data. Narayanan et al. (2023) proposed a new many-objective sine cosine algorithm (MaOSCA) that uses a reference point mechanism and information feedback principles to achieve efficient and robust performance.

Some scholars have also applied information entropy to denoising, feature extraction, and quantization of defect MFL signals. Zhu et al. (2019) took the signal-denoising method of broken wire damage of steel wire rope as the research background and used wavelet packet decomposition based on Shannon to denoise the signal. Wang et al. (2004) demonstrated the feasibility of one-dimensional and two-dimensional spectral entropy in identifying defect categories in MFL testing through experimental analysis. Dai et al. (2011) extracted features from the information entropy of MFL signals and combined the extracted signal feature quantities with BP networks to quantify the length and depth of defect signals. In 1977 Ralph Wiggins introduced the minimum entropy method into deconvolution problems when removing seismic signal features. He proposed the minimum entropy deconvolution theory (MED), which is of great value for solving deconvolution problems. Endo et al. (2007) proposed an autoregressive model enhancement method based on minimum

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