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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 entropy deconvolution for fault detection of gear teeth. Jiang (2013) proposed a method for early fault diagnosis of rolling bearings based on minimum entropy deconvolution and envelope spectrum analysis. Wei et al. (2008) applied minimum entropy deconvolution and sparse component analysis to ultrasonic NDT of pipelines.

In ultrasonic NDT and fault diagnosis, minimum entropy deconvolution has achieved good results in improving the resolution of ultrasonic signals and identifying impact signals caused by local faults. At present, there is no perfect method for preprocessing the MFL signal of rail surface defects. For this paper, we used minimum entropy deconvolution to enhance a weak signal under high-speed detection and to enhance the characteristics of small defect signals in the rail surface while suppressing background noise and improving detection rate.

RAIL MAGNETIC LEAKAGE SIGNAL PROCESSING BASED ON MINIMUM ENTROPY DECONVOLUTION

Rail is made of ferromagnetic materials, and after being locally magnetized under an external magnetic field, if the internal structure is uniform and defect free, the magnetic field lines will be evenly distributed in the rail. When a defect emerges or is located in the surface of the rail, distortion occurs when the magnetic field lines pass through, with some bending inside the material and the other refracting into the air on the material surface, forming a leakage in the magnetic field. After being collected by a Hall sensor, the defect signal can be obtained. The principle of magnetic leakage detection is shown in Figure 1.

Minimum entropy deconvolution can use the principle of minimum entropy to design optimal filters, highlighting the impulse components in the signal. As shown in Figure 2, the x-direction

Figure 1. Principle of magnetic leakage testing

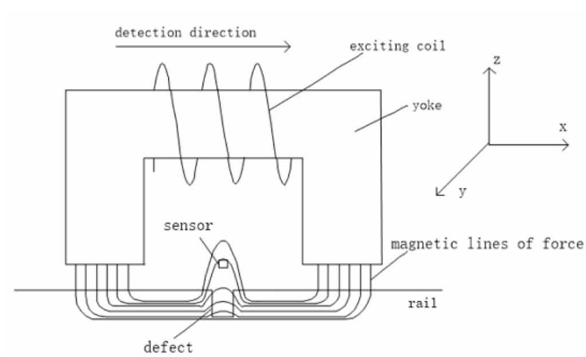
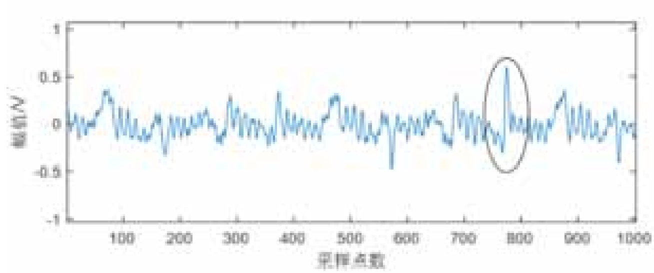


Figure 2. MFL signal with minor defects



leakage magnetic field signal of rail surface defect is similar to a pulse impact signal, but the common interference is not. Therefore, designing an optimal inverse filter and minimizing the entropy of the filtered signal enable a signal with enhanced defect x-direction leakage magnetic field signal to be obtained, while noise is suppressed owing to the less impulse components.

The essence of information entropy is an indicator that describes the distribution and complexity of information sources. In rail MFL detection, the minimum entropy deconvolution method assumes that the source signal $x(i)$ is a "sparse" sharp pulse sequence, which can be considered to have simple features, where the entropy value is small. After passing through system $h(n)$, the signal undergoes a process of entropy increase, and its output is $z(i)$, as shown in equation (1):

$$z\left(i\right) = h\left(n\right) \cdot x\left(i\right) \tag{1}$$

The output signal obtained by the MFL detection system is related to factors such as the equipment, velocity effect, and tested medium. The goal of preprocessing is to extract only signals related to defects. Given the output signal, obtaining the source signal only related to rail defects is the process of solving an inverse filter, which is a typical deconvolution problem. Therefore, the process of designing an optimal inverse filter and minimizing the entropy of the filtered signal enables a defect signal with obvious features to be obtained.

If we assume that the filter order $g(l)$ of the inverse filter is L, $y(i)$ is the output with minimum entropy after the inverse filter. $y(i)$ can restore the source signal $x(i)$, which can be described as shown in equation (2):

$$y\left(i\right) = \sum_{i=1}^{L} g\left(l\right) z\left(i-l\right) \approx \beta x\left(i-\tau\right) \tag{2}$$

When we restore the source signal $x(i)$, the focus is on restoring the filtered signal to its "simple features," where both amplitude and delay changes are allowed. The Eigenvector algorithm and objective function method are two common methods for implementing minimum entropy deconvolution. They are based on high-order statistics. The widely used method is the objective function method. Lee and Nandi (2000) used the k-order cumulant as the objective function of blind deconvolution, in the form shown in equation (3):

$$O_k\left(g\left(l\right)\right) = \sum_{i=1}^{N} y^k\left(i\right) / \left[\sum_{i=1}^{N} y^2\left(i\right)\right]^{k/2} \tag{3}$$

To design the optimal inverse filter $g(l)$ to minimize the entropy of the filtered signal, it is necessary to make the first derivative of the objective function 0, which can be described as shown in equation (4):

$$\partial\left(O_4\left(g\left(l\right)\right)\right) / \partial\left(g\left(l\right)\right) = 0 \tag{4}$$

From equation (2), we conclude that we can use the formula shown in equation (5):

$$\partial_y\left(i\right) / \partial_g\left(l\right) = z\left(i-l\right) \tag{5}$$

Therefore, we can obtain the matrix form as shown in equation (6):

$$b = Ag \tag{6}$$

among them:

$$b = \left[\sum_{i=1}^{N} y^2\left(i\right) / \sum_{i=1}^{N} y^4\left(i\right)\right] \sum_{i=1}^{N} y^3\left(i\right) z\left(i-l\right) \tag{7}$$

$$A = \sum_{i=1}^{N} z\left(i-l\right) z\left(i-p\right) \tag{8}$$

$$g = \sum_{p=1}^{L} g\left(p\right) \tag{9}$$

where b is the cross correlation matrix between the output signal $y(i)$ of the inverse filter and the input signal $z(i)$ as shown in equation (7). A is the Toeplitz autocorrelation matrix of the input signal of the inverse filter, as shown in equation (8), and g is the parameter of the inverse filter as shown in equation (9).

The minimum entropy deconvolution method is a process of searching for the optimal filter, and its algorithm process is as follows:

1. Calculate the Toeplitz autocorrelation matrix A and initialize the FIR filter parameter $g^{(0)}$.
2. According to equation (2), calculate the output signal $y^{(k)}$ using the known signal and FIR filtering parameter $g^{(k)}$, where k represents the number of cycles, k=0,1,2,...
3. Calculate the left term $b^{(k+1)}$ in equation (5) and use $g^{(k+1)} = A^{-1}b^{(k+1)}$ to calculate the new filter parameter $g^{(k+1)}$.
4. Calculate the cycle error, as shown in equation (10):

$$\begin{cases} E\left(err\right) = E\left[\left(g^{(k)} - \mu g^{(k-1)}\right) / \mu g^{(k-1)}\right] \\ \mu = \left(E\left(g^{(k-1)}\right)\right)^2 / \left(E\left(g^{(k)}\right)2\right)^{1/2} \end{cases} \tag{10}$$

5. Compare the error with the set convergence threshold. When the error is greater than the convergence threshold—i.e., $E\,(err)$>tolerance—proceed to step 2., and end the loop until the error is less than the convergence threshold. Finally, obtain the minimum entropy deconvolution FIR filter parameter $g^{(end)}$.
6. According to equation (2), $y^{(end)}$ can be calculated by using the known signal and the final FIR filtering parameter $g^{(end)}$, which is regarded as an approximation of $x(i)$.

EXPERIMENTATION RESULTS AND ANALYSIS

When an MFL detection system is used for high-speed rail inspection, the detection equipment is usually fixed on the detection carriage and scanned along the railway under the traction of the train (Hao et al., 2021). The equipment used in this experiment is a certain type of rail defect detection vehicle. The detection system includes a magnetic sensor probe, a signal conditioning circuit, a signal acquisition circuit, and a computer. The probe consists of three parts: a magnetizer used to provide excitation, SL-106C sensors used to detect leakage magnetic fields, and a sliding shoe. The conditioning circuit includes a high-pass filter circuit and an amplification circuit whose amplifier is AD620 with a magnification of 100. The signal acquisition circuit is ADLINK DAQ2208. As shown in Figure 3, the sensors are located between the magnetizer and the sliding shoe. After the circuit is inspected, playback software can be used to view suspected defect signals, and after manual review, defects can be corresponding to the signals.

The example of a natural defect is a small scratch that has been manually reviewed, with a length of approximately 18 mm, which is in the direction of the inspection vehicle traveling along the rail, and a width of approximately 15 mm, which is perpendicular to the direction of the inspection vehicle traveling along the rail, as shown in Figure 4. When the inspection vehicle passes through this defect, its speed is 45 km/h.

Figure 5 shows the original MFL signal obtained from 500 sampling points, denoted as S_0. The peak-to-peak V_{pd} of the defect signal is 0.529V, and the peak-to-peak V_{pn} of the background noise is 0.417V. The ratio of the peak-to-peak of the defect signal to the background noise is 1.27.

Figure 3. Flaw detection vehicle detection device

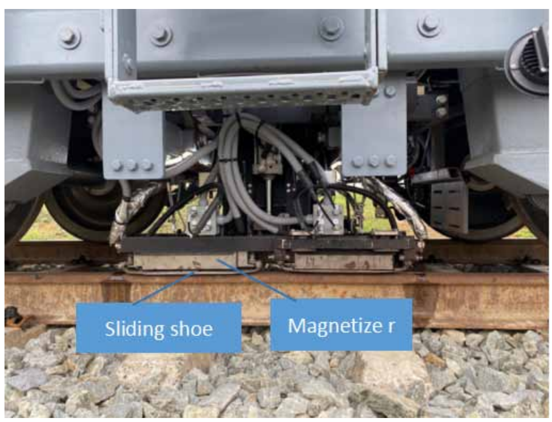


Figure 4. Examples of natural defects

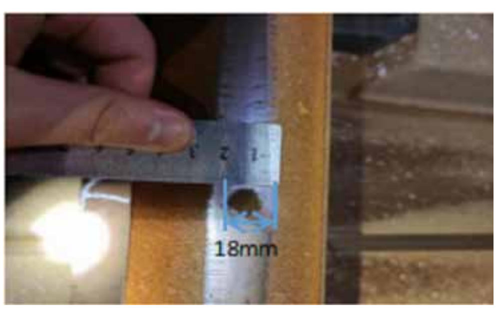
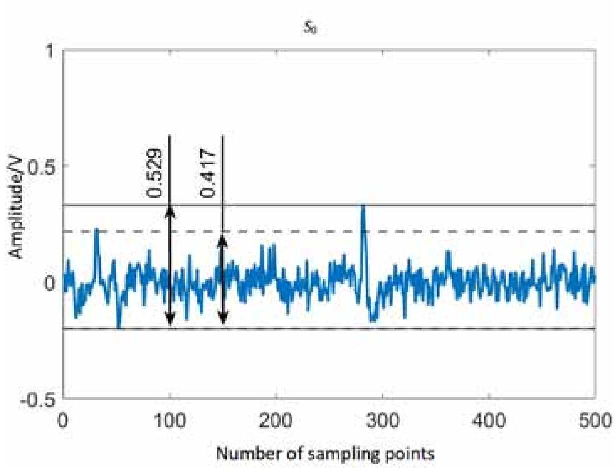


Figure 5. MFL raw signal



In the actual detection process, to screen out signals generated by minor defects, such as scratches and cracks in the surface of a rail, one method is to directly and manually replay the detected data. However, because of the long distance and large amount of data during rail inspection, errors may occur where there is a small difference between the peak and peak values of defect signals and background noises are similar as shown in Figure 5. Another method is to use a sliding window to slide on the sampling points to extract features and set a threshold for each feature. If the threshold is exceeded, it is considered damaged, but misjudgment may occur when the defect signal is minor or the noise is large.

According to the minimum entropy deconvolution method, the main influencing factors of filtering effectiveness are filter order L and convergence error E (*err*). When the filter order is 16, the signal has already shown very prominent impact components, and the noise signal is largely filtered out by the minimum entropy deconvolution operation. Higher order filters can further enhance the signal and suppress noise, but the overall change is not significant, so the order in this paper is set to 16. When the number of cycles k reaches a certain value, as long as the convergence error value is minor, the impact on the minimum entropy deconvolution is not significant, as in this paper, it is taken as 0.01.

After being filtered by the minimum entropy deconvolution algorithm, the defect signal is significantly enhanced, and the processed signal is marked as S_1 (MED), as shown in Figure 6. At this time, the peak-to-peak value of the defect signal V_{pd} is 0.966V, and the peak-to-peak value V_{pn} of the background noise is 0.48V. The peak-to-peak ratio of defect signal to background noise is 2.01.

The results of the experiment confirmed that this method has a good suppression effect on system noise, spatial magnetic field noise, magnetization, and material noise, whereas its suppression effect on lift-off interference caused by probe vibration and velocity noise is average. At present, high-speed railways generally use seamless steel rails, which have stable operating speed and less vibration, thus causing less interference to sampled signals. Therefore, this algorithm can filter out most background interference.

To measure the effectiveness of the minimum entropy deconvolution method in enhancing weak signals, we also used wavelet transform and median filtering methods to filter and compare the same MFL raw signals. The wavelet transform selects sym6 as the wavelet base and adopts soft threshold processing method. The processed result is shown in Figure 7, with the signal denoted as S_2 (WT). At this time, the peak-to-peak V_{pd} of the defect signal is 0.764V, the peak-to-peak V_{pn} of the background noise is 0.548V, and the ratio of the peak-to-peak value for the defect signal to the background noise is 1.39. The median filtering method sets the window length to 8, and the processed result is shown

Figure 6. Signal processed by minimum entropy deconvolution

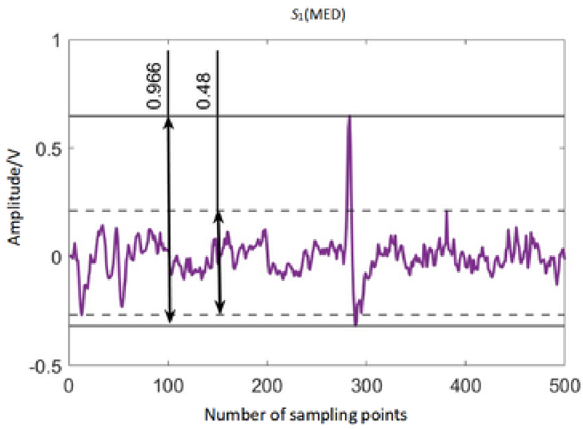
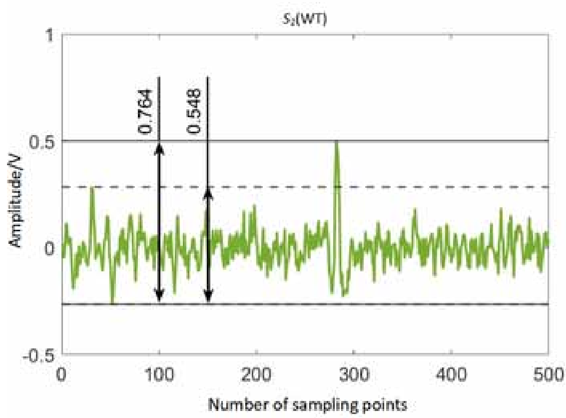


Figure 7. Signal processed by wavelet transform



in Figure 8. The signal is denoted as S_3 (MF), the peak-to-peak V_{pd} of the defect signal is 0.384V, the peak-to-peak V_{pn} of the background noise is 0.275V, and the peak-to-peak ratio of the defect signal to the background noise is 1.4.

Table 1 lists the peak-to-peak values of defect signals, background noise, and the ratio of defect signals to background noise in the four aforementioned types of signals. After being processed by the minimum entropy deconvolution algorithm, the peak-to-peak values significantly increase, and the defect signal is significantly enhanced.

Experiments have shown that when 500 data sampling points are processed, the operation time required by this method is about 140% of the wavelet transform method and about 160% of the median filtering method. However, the detection rate of minor defects is relatively increased by about 1.5 times, and the detection rate will also improve with the increase of data sampling points.

Figure 8. Signal processed by median filtering

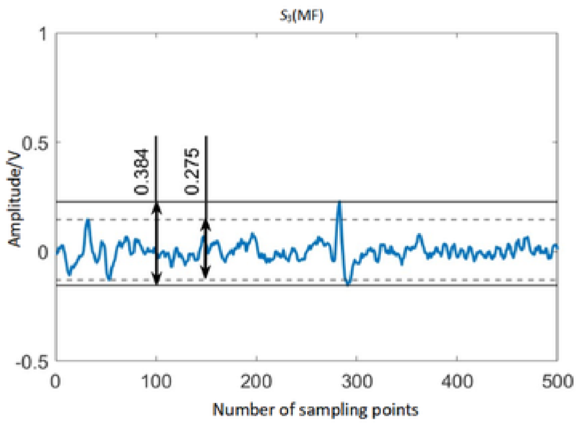


Table 1. A comparison of four signal peaks and peaks

	V_{pd}	V_{pn}	V_{pd} / V_{pn}
S_0	0.529	0.417	1.27
S_1(MED)	0.966	0.48	2.01
S_2(WT)	0.764	0.548	1.39
S_3(MF)	0.384	0.275	1.4

CONCLUSION

At present, under the MFL inspection of high-speed railways, the presence of various noises makes identifying defect signals difficult. For this paper, we used the minimum entropy deconvolution algorithm to process the MFL signal and analyze the MFL signal. We verified the method by the detection data of a natural defect in a rail. The results of a comparison with the wavelet transform method and median filtering methods show that the minimum entropy deconvolution algorithm has a significant enhancement effect on the MFL signal of rail surface defects, with an enhancement effect of 1.45 times that of wavelet transform and 1.44 times that of median filtering. This effect can provide support for improving the detection rate of minor defects on rail surface in future high-speed MFL inspections.

The signal processing method in this article has achieved certain results in the identification and denoising of minor defects, and has engineering practicality, but there are still some shortcomings. The number of the natural defect samples used to validate the denoising method in this article was limited, and subsequent analysis and verification should be conducted after accumulating a certain number of samples. After the defect signal is denoised, it needs to be evaluated and graded. We did not cover this process in this article, and this subject will be the focus of further research.

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