Magnetic anomaly of long track detection method based on wavelet combining with fractal for high speed maglev transit

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Abstract
A scheme of detecting magnetic field anomaly is proposed to find local short circuit faults in long stator cores of high speed maglev transit. And a composite magnetic anomaly signal processing method is designed based on wavelet with fractal, screening out a little anomalous data from massive data. First, suspicious data are quickly recognized by applying multiple fractal spectra, then being confirmed by wavelet modulus maxima calculation. The experiment results show that the method is immune to the fluctuation of 8–12 mm suspension gap and its hit rate can be improved by more than 66%.

Keywords
High speed maglev track, long stator, leakage magnetic field, multifractal spectrum, wavelet modulus maxima

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Introduction
According to “National Comprehensive Three-dimensional Transportation Network Planning Outline,” the layout of high speed maglev channels and construction of lines between mega cities are imperative. However, previous studies mainly focused on the suspension, ignoring the important component of maglev track. With the application of high-speed maglev traffic, the importance of track detection and maintenance will become prominent.¹ In Figure 1, unlike traditional wheel track, high speed maglev track is actually a long stator primary of synchronous linear motor, which is an important electrical component of the suspension and traction system in maglev transportation. Unfortunately, the focus of current track detection technology is still limited to geometric characteristics, ignoring its electrical properties.

Epoxies on the surface of iron core crack and fall off, resulting in short circuit between the silicon steel sheets, which is easily caused by the collision between the vehicle-track or environmental corrosion. If not repaired in time, it will lead to large distortion of traveling wave magnetic field, which directly affects the safety and stability of vehicle operation.² The research on this subject has a great significance to improve the operation efficiency of high-speed maglev traffic, avoid major safety accidents, and reduce economic losses.

The research shows the relationship between short circuit fault of cores and main Leakage Magnetic field of Traveling Wave (LMTW).³ A mounted magnetic field detection system (Figure 2) is designed by National University of Defense Technology to achieve dynamic and efficient monitoring for iron cores. It can efficiently analyze the condition of iron cores by LMTW closed with air.⁴ It’s a challenge, picking out the few anomalies from thousands of kilometers of massive data between mega cities.⁵

Common anomaly detection algorithms are statistics, data-driven and multiscale analysis. Statistics are suitable for detection of outliers.⁶ Because the anomaly of LMTW is faint, it’s easy to cause high false alarm. It’s difficult to implement the data-driven method because of the LMTW detection belonging to a typical under-sample problem.⁷ Multiscale analysis include spectrum analysis, wavelet analysis, Empirical Mode Decomposition (EMD) and fractal dimension or

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multifractal spectrum analysis.\textsuperscript{8} Spectrum analysis isn’t appropriate to LMTW with wide spectral range and complex interference; EMD has superior performance in filtering and denoising, but its mathematical basis is poor; Wavelet analysis is a time-scale analysis method, which is usually being adopted in signal singularity detection,\textsuperscript{9} such as radar target,\textsuperscript{10} aviation construction damage. Similarity-based fractal methods has a strong nonlinear representation. Literature\textsuperscript{11} analyzed simulation LMTW by Higuchi fractal dimension and proved it’s a typical fractal object. Location of distorted magnetic field can be effectively screened using fractal dimension. However, physical experiment was not involved.

Anomaly detection based on wavelet combining with fractal is a research hotspot in the engineering field.\textsuperscript{11} In medical bowel sound and heart sound anomaly detection,\textsuperscript{12,13} the higher-order statistical calculation based on fractal dimension and wavelet time-frequency analysis have been widely used to detect anomaly from normal signal under different noise levels and detection conditions.\textsuperscript{14} In seismic activity detection, Sanchez et al. proposed the EMD-FD algorithm by combining EMD with fractal theory for geomagnetic anomalies caused by low-frequency seismic activity, which uses EMD to remove background noise and combines three fractal dimension of Katz, Higuchi and Box to mine more information.\textsuperscript{15} In mineral exploration in surface covered areas, Guoxiong Chen proposed an anomaly extraction and identification method based on wavelet and fractal theory, which provides a new break through direction for identifying hidden ores by using wavelet transform to high light local details and using multiple fractal spectra to the intrinsic structure of the data.\textsuperscript{16}

The main contributions of this work can be summarized as follows:

1. Designed a compound anomaly signal processing method combined with the sensitivity of fractal to the internal law of massive data and the sensitivity of wavelet to local mutation (Figure 3). And it provides an efficient scheme for core fault detection of high-speed maglev track.
2. Fractal analysis is used to preliminary screening of massive data, and wavelet analysis is used to reinspection of suspicious data, which greatly improves detection efficiency and accuracy on the premise of ensuring the hit rate. The combination method is also suitable for other detection objects with huge amount of data. Constant False Alarm Rate (CFAR) is used to ensure that all anomaly data are detected in the preliminary screening, and the hit rate is improved by appropriately increasing false alarm.
3. The research also provides a new method for detecting core faults in large motor or damage detection in pipeline.

### Preliminary screening by multifractal spectrum

#### Fractal analysis of LMTW

The frequency spectrum of LMTW is analyzed. As shown in Figure 4, the frequency spectrum of $x$, $y$, and $z$ is similar. Among them, slopes of $a$–$f$ in the medium-
high frequency bands are \(-3 \sim -1\), which decays in inverse power law.\(^{13}\) So it has fractal characteristics above 7 Hz, and provides a basis for the application of fractal theory. In addition, from the slope of each frequency band, its fractal dimension isn’t unique, so it’s necessary to determine its multifractal characteristics.

Taking \(A_z\) as an example (LMTW is collected by Hall magnetic gradient tensor system, represented by \(A_x\), \(A_y\), and \(A_z\)), multifractal characteristics of LMTW are analyzed from definition. As shown in Figure 5, \(\ln x(q,e) - \ln e\) is approximately linear and convergent; \(q \sim e\) turns obviously nearby \(q = 0\); \(\alpha \sim f(\alpha)\) appears bell-shaped and satisfies the monotonic relationship. In conclusion, LMTW of high speed maglev track under normal conditions has multifractal characteristics.

### Objective function

The normal and anomaly data are distinguished by the characteristics of each spectrum after obtaining the multifractal spectrum corresponding to the magnetic field data of each track beam. Therefore, feature parameters are used to quantitatively describe the differences and similarities between spectra. The definition of characteristic parameters are as follows\(^{16}\):

(a) Spectral width \(\Delta \alpha\), \(\Delta \alpha = \alpha_{\text{max}} - \alpha_{\text{min}}\), \(\alpha_{\text{max}}\) and \(\alpha_{\text{min}}\) correspond to the strongest and weakest singular points in the multifractal spectrum;

(b) Max value of multifractal spectrum: \(f_{\text{max}}(\alpha)\);

(c) Difference of dimension between max and min probability subsets: \(\Delta f(\alpha) = f(\alpha_{\text{max}}) - f(\alpha_{\text{min}})\);

(d) Symmetric parameter: \(B = (\Delta \alpha_{\text{L}} - \Delta \alpha_{\text{R}})/\Delta \alpha\), \(\Delta \alpha_{\text{R}} = \alpha_{\text{max}} - \alpha_0\), \(\Delta \alpha_{\text{L}} = \alpha_0 - \alpha_{\text{min}}\), \(\alpha_0\) is the singularity index corresponding to the peak of multifractal spectrum.

After the fixed length signal is transformed into multifractal spectrum, \([\alpha_0, \alpha_{\text{max}}, \alpha_{\text{min}}, \Delta \alpha, f_{\text{max}}, \Delta f, B]\) is used to distinguish anomaly signal from normal signal. The absolute variation of each parameter is used to construct the objective function which is used as the input of CFAR detector to preliminarily screen anomaly signals.

\[
\Delta T = \Delta \alpha_0 + \Delta \alpha_{\text{max}} + \Delta \alpha_{\text{min}} + \Delta \alpha_{\text{L}} + \Delta \alpha_{\text{R}} + \Delta f + \Delta B
\]

\[
\Delta H = H - H_s\]

\(H\) represents any spectral parameters; \(H_s\) is the standard value of normal data, which is obtained through multiple experimental calibrations.

### Comparison of algorithms of multifractal spectrum

Using multifractal spectrum to screen massive data requires low computational complexity and strong robustness. Calculation methods include Box-counting, Moment, WTMM, Wavelet Leader and MF-DFA, in which WTMM based on CWT lacks theoretical basis.
with large computational complexity, and MF-DFA is prone to poor stability of calculation with different segmentation scale. So, Box-counting, Moment and Wavelet Leader are involved in this paper.

Algorithm time complexity analysis: Time complexity, referring to the running time of the algorithm, is usually described by theoretical calculation complexity ($T_n$) and actual running time ($t$). This paper compares $T_n$ and $t$ of the above three algorithms when inputting the same signal. The results are shown in Table 1.

The calculation parameters of $T_n$: boxes ($N$), $q(2n + 1)$, the data length ($L$), and wavelet decomposition layers ($d$). The object of multifractal analysis is the magnetic field data corresponding to track beam length 24.768 m. Because of spatial sampling, the length of data is same. When $n = 20$ is selected, $T_n$ of Box-counting depends on $N$, and $T_n$ of Wavelet Leader depends on $d$. In practice, $N$ is 200 and $d$ is 4. $T_n$ is as follows: Box-counting < Moment < Wavelet Leader.

Algorithm robustness analysis: The calculation results of multifractal spectrum are closely related to its components. If the signal is mixed with different degrees of noise or periodic components, calculation results may have various degrees of deviation. The robustness is estimated according to the influence of the mixed components on different algorithms. The standard and mixed components are as follows:

Table 1. Time complexity of different algorithms.

|                | Box-counting | Moment | Wavelet Leader |
|----------------|--------------|--------|----------------|
| $T_n$          | $O((5N + 1)(2n + 1)+L)$ | $O(L(2n+3))$ | $O(Lnd(2n+1))$ |
| $t$/s          | 1.05         | 2.49   | 11.74          |

Figure 5. Multifractal analysis results of LMTW: (a) original signal, (b) $\ln \chi(q,e) - \ln e$, (c) $\tau_q - q$, and (d) multifractal spectrum.

After mixing different intensities of noise signal, two groups of fractal spectrum calculated by Box-counting have obvious aliasing, while the fractal spectrum calculated by Moment and the Wavelet Leader have high discrimination. As shown in Figure 6, by calculating objective function, it’s found that the discrimination of Moment to anomaly signals is more obvious than Wavelet Leader.

(1) Multifractal spectrum after mixing white Gaussian noise

(2) Multifractal spectrum after mixing sin periodic signals
the same impact on normal and anomaly signal, but it still has obvious discrimination. So mixing small amplitude periodic signals will not affect the effectiveness of two methods.

According to the analysis results of time complexity and robustness, Moment has the same stability as Wavelet Leader, but has significant advantages in computational efficiency. Therefore, Moment is selected to calculate the multifractal spectrum of LMTW.

Preliminary screening mechanism by CFAR

The purpose of primary screening of massive data is to greatly reduce the amount of data sent to reinspection step. The traditional fixed threshold has poor adaptability and is prone to miss rate or false alarm. CFAR used in radar multi-target detection, balances the relationship between “miss rate” and “false alarm” by Neyman Pearson. It can adaptively adjust comparison threshold according to the input to improve hit rate as much as possible within the set false alarm range.19 Classical detectors include CA-CFAR, GO-CFAR, and SO-CFAR which have similar computational complexity. Among them, SO-CFAR has the largest detection probability for multiple anomaly targets. Therefore, SO-CFAR is selected to detect the anomaly multifractal spectrum in this paper.

Reinspection by wavelet modulus maxima

The LMTW caused by the iron core of short circuit shows an anomaly mutation. To judge whether the iron core is damaged is to determine whether the corresponding magnetic field signal has singularity. Compared with the traditional Fourier transform, wavelet analysis has good time-frequency localization ability. It can filter the noise and retain abrupt components of the signal. To a certain extent, it avoids the blurring of abrupt components by low-pass filtering. Binary wavelet transform (BWT) only discretizes scale parameters and has time-shift invariance. So it’s superior to discrete wavelet transform (DWT) in signal singularity detection and adopted in the Reinspection process.20

Figure 6. Variation of spectral parameters with intensity of white Gaussian noise: (a) Moment and (b) Wavelet Leader.

Figure 7. Variation of spectral parameters with periodic signal frequency: (a) Moment and (b) Wavelet Leader.
Pretreatment process

The object of wavelet analysis is Ax, Ay and Az corresponding to track beam of 24.768 m. On the one hand, the magnetic gradient is calculated by the spatial difference approximation method, which strengthens characteristics of the magnetic field anomaly caused by cores damage. On the other hand, because the gradient is more violent than amplitude, it leads into high-frequency noise. In addition, the magnetic sensor array is installed close to electromagnets. The high-frequency magnetic modulation interference, caused by chopper and the natural noise, seriously impacts on the judgment of anomaly signal and must be filtered.

Wavelet threshold has higher stability, lower computational complexity and stronger applicability to low SNR signals. It’s denoising process is shown in Figure 9. The key lies in the selection of wavelet basis function, wavelet coefs processing strategy and threshold estimation method.

Selection of wavelet basis function: The essence of wavelet coefs is to quantify the similarity between wavelet basis function and signal. In addition, the length of support set, regularity, vanishing moment and symmetry of wavelet basis function all determine quality of wavelet transform. The performance comparison of common wavelet basis functions is shown in Table 2.

Combined with simulation results in Luo, dbN, symN, coifN, and bior with high similarity are selected to analyze the magnetic gradient tensor analytical signal (Ax). Sum of Squared Errors (SSE) of wavelet decomposition and artificial fitting result are used to characterize the advantages and disadvantages of decomposition results. They are shown in Figure 9. To sum up, the approximate coefs of symN and coifN are the closest to fitting results. Compare the length of support set and vanishing moment, and select symN wavelet basis function for BWT, with order n = 4.

Selection of threshold and threshold function: In wavelet threshold filtering, threshold and threshold function are two basic elements, which determine the final denoising effect of magnetic anomaly signal. At present, there are three kinds of thresholds proposed: Sgtwolog, Rigrsure, and Heurshrink. In the above estimation methods, the fixed threshold and minimum maximum variance criterion are characterized by “over strangulation,” which can eliminate more noise and may also remove useful high-frequency signals. The unbiased risk estimation criterion and hybrid criterion tend to “over reservation,” and only part of the coefs are set to zero, which is suitable for the situation that frequency distinction between useful signal and noise is obvious and SNR is high.

The threshold function determines the processing strategy of wavelet coefs greater or less than the threshold. Compared with hard threshold, the processed signal of soft threshold is smoother, but it’s very unfavorable to the anomaly detection. Hard threshold can retain more extreme points, which benefits the

Table 2. Comparison of performance parameters of wavelet basis functions.

| Name       | Length of support set | Vanishing moment | Symmetry | Orthogonality | Regularity | Comprehensive evaluation            |
|------------|-----------------------|------------------|----------|---------------|------------|--------------------------------------|
| harr       | 1                     | 1                | Yes      | Yes           | —          | Time domain discontinuity            |
| dbN        | 2N – 1                | N                | Approximate | Yes           | Yes        | Strong localization ability,         |
| symN       | 2N – 1                | N                | Approximate | Yes           | Yes        | The phase distortion:                |
| coifN      | 6N – 1                | 2N               | Approximate | Yes           | Yes        | coifN < symN < dbN                   |
| mexicanHat | Limited               | —                | Yes      | No            | —          | Non orthogonal,                      |
| morlet     | Limited               | —                | Yes      | No            | —          | serious information redundancy      |
| meyer      | Limited               | —                | Yes      | No            | —          | Used for decomposition and reconstruction |
| biorN.rNd  | 2N + 1                | N – 1            | No       | Yes           | Yes        |                                      |
extraction of anomaly features according to the discrimination of wavelet modulus maximum line. Therefore, this paper selects fix hard threshold processing method to directly set the wavelet coefs determined to be related to noise, so as to reduce number of extreme points caused by noise as much as possible.

**Anomaly detection process of wavelet modulus maxima**

Actual signals are often mixed with various noises and expected signals. The anomaly detection based on wavelet modulus maxima can accurately extract the signal from noises according to the different propagation characteristics of noise and signal in wavelet transform. The detection process is shown in Figure 10.

For actual signals, not all modulus maxima lines linked to noises will be interrupted, and modulus maxima lines linked to signals are connected. Modulus maxima points linked to signal have higher correlation and more concentrated positions than noises. In reasonable search range, with gradual reduction of the search range, number of modulus maxima lines linked to signal tends to be stable. However, due to the strong randomness of distribution position of noise’s modulus maxima points, number of modulus maxima lines tends to decrease.

**Experimental results**

**Ground verification device**

Based on traveling wave magnetic field is regular, the proposed anomaly detection method can be equivalently verified through transformation model of ground detection and on-board detection data. Figure 11 shows the ground validation device include five parts: linear motor primary, magnetic sensors array, mobile platform, transducer, and data acquisition module. The transducer is used to excite the linear motor primary to simulate LMTW. The detection distance between the measurement array and the stator is controlled by the vertical moving module, and the horizontal moving module is driven to scan the stator surface at low speed. The magnetic gradient tensor signal is synchronously detected and sent to the upper Computer for storage and display.

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Figure 10. Detection process of wavelet modulus maxima.

![Detecting Process of Wavelet Modulus Maxima](image)

Figure 11. Ground verification device for measuring LMTW: (a) structural composition of verification device and (b) verification device.
Verification of compound magnetic anomaly detection method

In Figure 11, the 12th tooth of linear motor stator is damaged to simulate the short circuit fault of iron core, with the size of about 42×7 mm located 141 mm. Prewitt magnetic gradient tensor array is used to scan the stator surface at low speed, and the magnetic field data of normal and damaged stator are collected respectively. The analytical signals $A_x$, $A_y$, and $A_z$ are further calculated. Because the magnetic field amplitude at both ends of the linear stator has a large attenuation, it is relatively stable only in the range of 90~210 mm, so only the magnetic field data in this range are intercepted.

Preliminary screening results: Respectively collect 200 groups of normal magnetic field data and 5 groups of anomaly magnetic field data at the detection distance of 8~12 mm. Standard fractal spectral parameters in Table 3 are obtained by averaging parameters of 200 groups of normal magnetic field data. The difference of spectral parameters in $x$, $y$, and $z$ is mainly in symmetry.

Five position numbers, 146, 76, 124, 164, and 55 are randomly generated, and the anomaly data obtained from different detection distances of 8~12 mm are inserted. Spectral parameters are calculated respectively for each group, and obtained the objective function value. The SO-CFAR is used to calculate the adaptive threshold. Results in different directions are shown in Figure 12. The false alarm is set to 5%, the sliding window size is 30, and the extension length at the end is 20.

The comprehensive judgment basis: if two or more directions of $x$, $y$, and $z$ are judged as anomaly, the comprehensive result is anomaly, otherwise it is normal. The comprehensive judgment results show that the data NO.55 (12 mm), 76 (9 mm), 77 (false alarm), 124 (10 mm), 133 (false alarm), 146 (8 mm), and 164 (11 mm) have short circuit fault of iron core, the anomaly hit rate is 100% and the false alarm is 1%.

### Table 3. Standard fractal spectral parameters.

|  | $a_0$ | $a_{max}$ | $a_{min}$ | $\Delta a$ | $f_{max}$ | $\Delta f$ | $B$  |
|---|------|---------|---------|--------|--------|--------|-----|
| $x$ | 1.0094 | 1.2269 | 0.9253 | 0.3016 | 1.0000 | -0.3564 | -0.4246 |
| $y$ | 1.0137 | 1.2124 | 0.9042 | 0.3082 | 1.0000 | -0.3021 | -0.2877 |
| $z$ | 1.0118 | 1.2387 | 0.9072 | 0.3315 | 1.0000 | -0.2650 | -0.3710 |

**Figure 12.** Preliminary screening results of multifractal, and “1” indicates the data contains abnormal information: (a) detection results of $x$, (b) detection results of $y$, (c) detection results of $z$, and (d) comprehensive detection results.
Experimental conclusion: the magnetic anomaly screening based on multifractal spectrum can effectively detect the short circuit fault of iron core, and is not affected by the fluctuation of vertical detection distance.

Reinspection results: According to the detection process shown in Figure 3, send the suspicious data to reinspection for review.

As shown in Figure 13, taking \( A_x \) as an example, only modulus maxima points are retained. From Figure 13(a), (b), (d), (e), (f), they show that the distribution positions of modulus maxima points are highly correlated to the data containing the real anomaly signal on different scales. The distribution of modulus maxima caused by noise has no clear law.

As shown in Figure 14, compared with the data of magnetic anomaly signal, the proportion of the number of modulus maximum lines of false alarm data NO.77 and 133 decreases significantly with the reduction of search range, or itself is very small. Set the threshold value to 30%, and synthesize analysis results in different directions. Finally, it can be determined that the data of NO.55, 76, 124, 146, and 164 contain magnetic anomaly information, while NO.77 and 133 are obviously false alarms. At the same time, according to the centralized position of modulus maximum line, it can be determined that the position of short circuit fault is 129–157 mm, the deviation from the position (141 mm) of short circuit fault is within two coggings.

Experimental conclusion: the reinspection method based on wavelet modulus maxima can further accurately distinguish suspicious data, improve detection accuracy and reduce false alarm. Combining with preliminary screening, it can realize fast and accurate detection of massive data.

Comparative experiment of phase comparison method: Literature\(^\text{23}\) proposed a magnetic field phase comparison method. The method is based on sinusoidal periodic distribution of LMTW, calculates the phase by anti-sine, and detects the fault according to the change of signal phase. The principle is shown in Figure 15, The red part is the fault points.

Using a in-line array composed of 8 Hall magnetic sensors, 200 groups of magnetic field data required by the phase comparison method are obtained on the experimental platform shown in Figure 11. In the same way, the magnetic field data collected in the damage area are inserted in NO.55, 76, 124, 146, and 164. In simultaneous interpreting, the output value of different sensors is sinusoidal trend change. Sine fitting of each group is made. Calculate the deviation phase and standard phase according to the fitting result. The absolute value of the max phase deviation is shown in Figure 16. Because the phase comparison method only focuses on the relative amplitude change between sensors, the normalization operation is carried out before sine fitting.

As shown in Figure 16, phase deviation caused by damage of iron core is only obvious in the \( z \), and only the data No. 55, 124, and 146 are detected. The anomaly hit rate of \( z \) is 60%, and the \( x \) and \( y \) are 20% and 0, which has serious miss rate. The standard sine variation of space magnetic field is the premise of phase comparison method. But in practice, the detection accuracy of phase comparison method is seriously affected due to cogging structure. The method proposed in this paper...
only considers the difference between the anomaly and normal magnetic field in both preliminary screening and reinspection process. It has obvious advantages over the phase comparison method.

Conclusions

Aiming at fast selection of a few anomaly targets in massive data, using the similarity of LMTW, suspicious data is identified through multifractal spectrum characteristics. Using BWT to signal singularity, suspicious data is accurately detected by distribution of wavelet modulus maxima at different scales. The proposed method can adapt to 8–12 mm detection distances, and its hit rate can be improved by more than 66%. During implementation, three points should be paid attention to:

The spectral parameters should be calibrated with massive data, which determines the hit rate of preliminary screening. Its limitation is that the parameters need to be calibrated according to the actual samples and can’t be directly applied.

The CFAR is inversely proportional to the detection efficiency of the preliminary screening, and the false alarm should be controlled within 20%.

Figure 14. Relationship between the number of wavelet modulus maxima lines and search range: (a) $A_x$, (b) $A_y$, and (c) $A_z$.

Figure 15. Schematic diagram of phase comparison method using in-line magnetic sensing array: (a) normal condition and (b) abnormal condition.

The analysis method based on the similarity of magnetic field waveform can also be applied to the field of large motor fault detection, pipeline detection or geomagnetic anomaly detection.
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Figure 16. Results of phase comparison method: (a) detection results of x, (b) detection results of y, and (c) detection results of z.
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