Received February 19, 2021, accepted March 6, 2021, date of publication March 10, 2021, date of current version June 23, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3065044

Adaptive Filtering Method of MFL Signal on Rail Top Surface Defect Detection

KAILUN JI[1], PING WANG[1], YINLIANG JIA[1], YUNFEI YE[2], AND SHUNYI DING[1]

[1]College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 211000, China
[2]School of Intelligent Engineering, Nanjing Institute of Railway Technology, Nanjing 210031, China

Corresponding author: Kailun Ji (jkevin1898@outlook.com)

This work was supported in part by the Ministry of Science and Technology Special Scientific Instrument Development under Grant 2016YFF0103702, in part by the National Natural Science Foundation under Grant 61527803, in part by the National Key Research and Development Program of China under Grant 2018YFB2100903, and in part by the China Railway Corporation, under Grant 2017G003-D.

ABSTRACT Magnetic flux leakage (MFL) detection technology provides an effective method to conduct high-speed detection of the damage suffered by rail surface. With regard to high-speed detection, there is frequently a complex noise contained in the magnetic signal of railway leakage, which is similar to the amplitude of defect and the overlaps of frequency spectrum. In this paper, an improved adaptive filtering method is proposed to solve the problem caused by filtering the MFL signal on the rail top surface. Through the characteristics of distribution shown by defects on the top surface of the railway and those of the data collected by the rail top array sensor, this method is applied to construct a virtual channel containing almost only interference signals but no defects. Then, in combination with the adaptive filtering algorithm, the virtual channel signal is taken as the reference input of the adaptive canceller, each single channel MFL signal is taken as the original input of the adaptive canceller, and the filtered MFL signal is taken as the output. Then, the MFL signal of rail top is collected by the train at the speed of 30km / h on the manual calibration line. According to the experimental results, the noise intensity of MFL signal is reduced by up to 81.44%. In addition, the filtering method is adopted to process MFL signals with different directions and varying detection speed. As indicated by the results, the noise intensity of MFL signal is reduced by more than 74%.

INDEX TERMS High speed rail detection, magnetic flux leakage signal, adaptive filtering algorithm, reference signal, adaptive noise canceller.

I. INTRODUCTION

At present, the non-destructive testing technology of magnetic flux leakage (MFL) [1] has been widely applied to conduct non-destructive test on the surface cracks of such ferromagnetic parts as rails due to the simple structure of its sensor, the high sensitivity of detection and the capability of non-contact detection. In the course of high-speed MFL inspection conducted on rails, there will be a lot of noise contained in the signal of MFL. Currently, the main problem with the MFL signal is that there are complex vibrations [2], [3] and other forms of disturbances caused during the process of high-speed inspection. As for the high-speed MFL inspection on rails, there will be many kinds of noise contained in the MFL signal. Firstly, the non-stationary random vibration caused to the mechanical structure of locomotive and the rails with a certain degree of surface roughness can affect the strength of leakage magnetic field and background magnetic field respectively, as evidenced by the change to the lift-off value of the sensor from the rails surface and the yoke lift-off value, as a result of which the vibration noise is coupled [2], [3] to the signal of magnetic leakage detection. Secondly, with the increase of speed, the distribution of magnetic field intensity in rails is made uneven due to the impact of eddy current. Thirdly, it is inevitable for MFL acquisition system to be affected by such electromagnetic interference as white noise and power frequency interference in the environment. In respect of MFL signal processing, various methods have been proposed to extract the signal of rail defects from the complex interference without changing the shape of the defect. By means of time-frequency analysis, median and adaptive filtering, as well as interpolation,

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaokang Yin.

Mao Bingyi preprocessed MFL detection signals [4]. Daniel J adopted a variety of different wavelet-based denoising techniques to remove noise from the raw data [5]. However, the limitation is that there is no effective solution to filtering out the noise overlapping with the power spectrum of the defect. By means of Kalman filtering, Erazo Kalil proposed Vibration-based structural health monitoring in the context of ever-changing environmental conditions [6]. Based on time-sequenced adaptive filtering, Fotiadou E proposed the enhancement of low-quality fetal electrocardiogram [7]. Bai Liming applied an adaptive filter to eliminate ECG motion artifact interference [8]. The limitation imposed on this method lies in the ability to obtain effective reference signals from the hardware. In the rail detection system, however, each sensor is allowed the opportunity to detect the defect, which means that the output of each sensor is not suitable as a reference signal. As mentioned above, MFL signals contain complex noise under the condition of high-speed rails inspection. These noises show large amplitudes, with the power spectra of these noise overlapping those of useful signals. Therefore, the aforementioned methods are subject to various limitations, respectively. Moreover, most of the above-mentioned methods are intended for an environment with relatively low levels of noise intensity, while the frequency component of the interference signal is complex and the noise intensity is high for the high-speed detection of rails.

With the development of MFL detection [9]–[11] technology intended for rail inspection, there have been various requirements placed on rail inspection equipment, for example, high speed, high efficiency and high resolution. In respect of signal processing, it is inevitable for these requirements to result in the circumstance where high-intensity and non-stationary random noise is made and the power spectrum of the noise overlaps with useful signals. The noise of these types can cause serious interference with signal analysis and defect reconstruction. Besides, they play a major role in hindering the application of MFL detection technology in the field of rail inspection. Having a significant adverse effect on signal analysis and signal inversion defect process, this is also the main obstacle to the application of MFL nondestructive testing technology in rail inspection. In order to address the above-mentioned issues, this paper proposes an improved adaptive filtering method by considering the limitations on the above-mentioned methods, so as to extract pure defects from a large amount of complex noise. The filtering algorithm is verified by MFL data used for detecting rail surface cracks at the speed of 10 km/h, 20 km/h and 30 km/h, respectively. The rest of this paper is organized as follows. Section 2 introduces the theoretical background and methodology of MFL detection and adaptive filtering. Section 3 elaborates on the improved adaptive filtering method and experiments. In Section 4, the analytical results obtained from the experiment are presented. Section 5 introduces a method used to conduct quantitative analysis of filtering effects and to evaluate the filtering effect and suitability of the method. With different processing results compared and discussed, a conclusion is drawn and the future direction of works is indicated in Section 6.

II. THEORETICAL ANALYSIS OF MFL DETECTION

A. PRINCIPLE BACKGROUND OF MFL DETECTION

As for the principle of MFL detection [12], it is based on the fact that the magnetic permeability of ferromagnetic materials (such as steel) is clearly superior to other varieties of non-ferromagnetic media, such as air. When the magnetic field line of an item encounters an internal defect and there is discontinuity occurring, the magnetic field line will be distorted to cause change to magnetic field as can be detected by the sensor. In general, the rail is made from ferromagnetic material. After the railway is locally magnetized, a leakage magnetic field will be formed on the surface if there is a defect developing on the surface of the railway. There is a close association between the size and distribution of the leakage magnetic field signal and the defect, while the width of the defect makes little difference to the amplitude of MFL signal. Therefore, by picking up the leakage magnetic field with a magnetic detecting element, such as a Hall element, the information about various defects can be acquired for subsequent analysis. Fig. 1 (a) shows the basic principle of MFL detection of rail.

As shown in Fig. 1(a), after the magnetizing device is partially magnetized, if there is no defect developing in the rail, no overflow will occur to magnetic flux and magnetic leakage field will be formed. Thus, it is unlikely for the Hall sensor to detect MFL signal. Conversely, if the rail contains defect, the Hall sensor is able to detect it.

Fig. 1(b) shows the flowchart of how the array sensor conducts detection within the rail MFL detection system. In order to prevent missed inspection, the array sensor covers the top width of the rail. In the course of detection, the n Hall sensors are deployed in a row perpendicular to the direction of travel of the train to collect MFL signal from the top surface of the rail. Then, the flowchart of signal conditioning for MFL detection shown in Fig. 1(c) is used to perform signal conditioning, with the signals amplified, stored, and finally converted into a digital voltage signal.

B. ANALYSIS OF NOISE

When MFL detection method is adopted to detect the defects of rail, a variety of noises are introduced in the collection and transmission of MFL signals. Firstly, in the signal acquisition phase, due to the vibration of the high-speed train and the vibration of the transmission equipment, the complex mechanical vibration of the train will cause the detection system to vibrate [13]–[15]. As a result, the yoke lift-off and the sensor lift-off will change, thus making difference to the background magnetic field. Due to the variation in background magnetic field acquisition, the vibration interference with different frequency and large amplitude is superimposed on MFL signal. Secondly, the leakage magnetic field of the

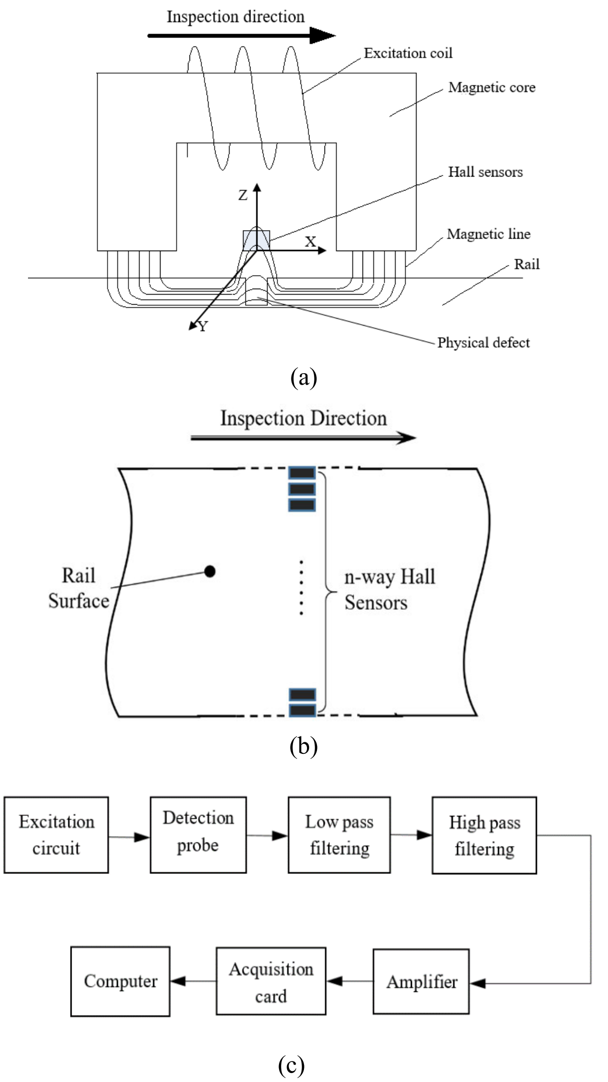


FIGURE 1. MFL detection system: (a) Probe for MFL detection; (b) Array sensor distribution map; (c) Flowchart of signal conditioning for MFL detection.

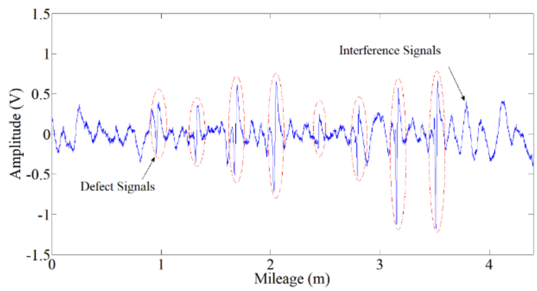


FIGURE 2. MFL signal with strong disturbance at 30km/h.

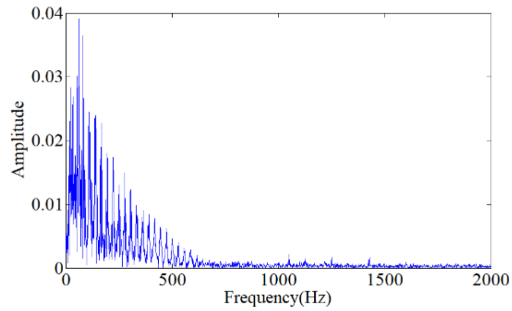


FIGURE 3. Spectrum analysis of the original signal.

defect is a spatial magnetic field. In case of other electrical devices around the detection device, for example, transformer, motor, a magnetic field will be generated in space. If there are no measures taken, it may suffer disturbance when a defective leakage magnetic field signal is picked up with a Hall element. In the data transmission phase, after the magnetic field signal is converted into an electrical signal by the Hall sensor, it needs to be processed by analog and digital circuits, such as amplification, filtering, A/D conversion, *etc*. In this process, circuit noise and power frequency interference will be superimposed on the defect using various methods.

The overall effect produced by the detection system is that the defects are disturbed by complex noise, which makes them difficult to distinguish between. As shown in Fig. 2, the signals in ellipses are the defects and the other signals are the interference signals showing no periodicity but similar amplitude. This is clearly adverse to the effective detection and quantitative analysis of rail defects since the signals of minor defect are easy to be submerged and difficult to identify. Meanwhile, their frequencies overlap each other according to the spectral analysis of the MFL signal, as shown in Fig. 3. Therefore, it is difficult for the MFL signal to be effectively filtered out through frequency domain filtering or time-frequency filtering alone. In general, the noise of MFL testing system of the rail involves not only electrical noise, such as power frequency interference and ground potential difference noise, but also mechanical noise, such as the vibration of the locomotive equipment, triboelectric effect, and the movement of the conductor in the magnetic field. Therefore, it is essential to ensure the effective filtering of MFL signals, which is difficult to achieve though.

C. THE METHODOLOGY OF THE ADAPTIVE NOISE CANCELLER

At present, adaptive filters [16], [17] have been widely applied in such fields as signal detection, noise removal, prediction, and so on. They are especially suitable for non-stationary signal processing. This filter is characterized by a learning function. With the desired signal as a "mentor", the input signal is used to estimate the desired signal through the filter output, and the filter coefficients are gradually updated to make the filter increasingly approach the optimal filter. In this study, one of the applications of adaptive filters - adaptive interference cancellers are adopted. Fig. 4 shows the structure of the adaptive canceller.

The original input d_j as shown in the Fig. 4 is comprised of the expected signal s of additive noise v_0 pollution. Reference input is noise v_1, which is related to interference signal v_0 and s. System output is $e_j = d_j - y_j$, $y_j = W_j^T X_j$.

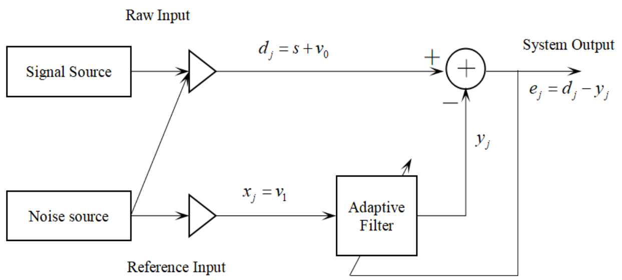


FIGURE 4. Adaptive canceller.

The adaptive process is the automatic regulation W_j,which leads to $E[e_j^2] = min$. From Fig. 4, it can be obtained that,

$$E[e_j^2] = E[s^2] + E[(v_0 - y_j)^2] - 2E[s(v_0 - y_j)] \tag{1}$$

It is potentially desirable to set s, v_0, v_1 as stationary stochastic processes with zero mean. Since s is irrelevant to v_0, and v_0 is related to v_1, the signal power $E[s^2]$ in the upper formula is irrelevant to W_j. Thus,

$$E[e_j^2]_{min} = E\left[s^2\right] + E[(v_0 - y_i)^2]_{min} \tag{2}$$

$$E[\left(e_j - y_i\right)^2]_{min} = E[(v_0 - y_i)^2]_{min} \tag{3}$$

When $E[(v_0 - y_j)^2]$ is minimized, $E[\left(e_j - y_i\right)^2]$ is minimized, which means e_j, as the minimum mean square error, tends to be s, so that the best-case scenario is

$$y_i = v_0 \tag{4}$$

So

$$e_j = s \tag{5}$$

From formulas (4) and (5), it can be seen that adaptive filtering is capable to extract the defect from the noise as long as the reference signal related to the noise in the MFL signal and independent of the defect is obtained. However, it requires some skills to find a reasonable reference signal [18]. In this study, it is proposed that the MFL signals of the array sensors are applied to extract the voltage amplitude with the smallest absolute value at each moment to construct a virtual channel, which is the complete reference signal. Next, it will be demonstrated how to construct a virtual channel and an adaptive noise canceller.

III. IMPROVED ADAPTIVE FILTERING METHOD

The advantage of adaptive filtering is reflected in its capability to filter random signals without knowing the apriori statistical characteristics of signals and noise. However, it is necessary to collect a piece of channel data containing only interference information and no defect information as a reference signal to filter out leakage flux. To achieve effective filtering, the interference information carried by the signal includes the information about defect. In practice, however, the existence of defects on the unknown section of railway is randomized. Therefore, it is possible for each channel in the array sensor to detect the defect. As a result, it can be found out that only the interference information is contained and the defect information is excluded. Thus, the channel presents an urgent problem to resolve.

According to the characteristics shown by noise, the procedures of denoising the MFL signal are designed, as shown in Fig. 5.

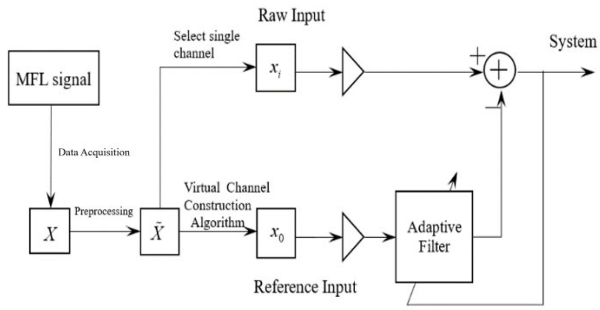


FIGURE 5. MFL signal denoising process.

Stage 1: Preprocessing

Through the MFL acquisition system shown in Fig. 1, a MFL signal is obtained, including $X(1), X(2), \ldots, X(p), \ldots, X(n)$,. The MFL signal collected by each Hall sensor is, where dim(X)=n and p denotes the channel number. It is one of 1, 2 to n.

The MFL signals are denoised by means of amplifying circuit and band-pass filtering to obtain $\tilde{X}$ [19]. The denoising performed by preprocessing is purposed to filter out the detail components (the high frequency noise and direct component) from MFL signal while preserving the contour information in the signal (the low frequency defect).

Stage 2: Interference reconstruction

As is mentioned above, an appropriate reference signal is required before adaptive filtering is performed.

When there is nothing but noise, all sensors can detect noise simultaneously, which is because all sensors are situated in the background magnetic field with almost the same background. However, due to varying degrees of impact caused by noise, the amplitude of signal shows difference. When a defect occurs, in order for the sensor to overcome the defect, the MFL signal collected is affected by both the magnetic field leakage and noise. While for the sensor not overcoming the defect, the MFL signal collected is affected only by noise. It is also found out that the amplitude of defect MFL signals with noise is generally greater than that of noise MFL signals. This is because the defect with noise is consistently larger than the only noise at the same time, while the minimum output value of all array sensors is the noise at all times. Unless all sensors detect the same defect at the same time, it is rare for the natural cracks in the state of nature to show the regular defects that are perpendicular to the direction of travel for train and cover the rail width (the same distribution as transverse array sensors). Therefore, the minimum absolute value of each moment is selected to construct a virtual noise channel.

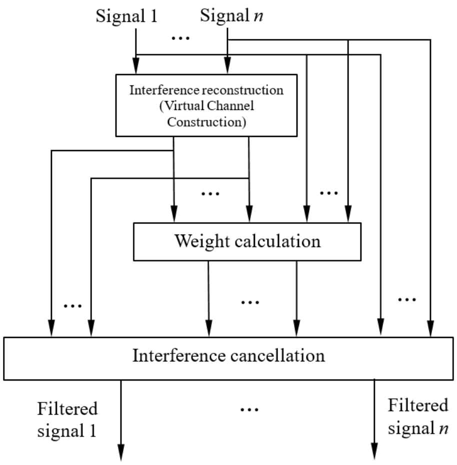


FIGURE 6. The process of multichannel adaptive filtering.

Stage 3: Interference cancellation

An adaptive noise canceller is built in [20], [21]. Fig. 6 shows the process of multichannel adaptive filtering. Based on the adaptive filtering algorithm, the virtual channel construction algorithm is applied to construct the adaptive noise canceller, and the magnetic signal of rail leakage is filtered for a second time. With the virtual channel obtained above taken as the reference signal of the adaptive filter, single channel filtering is performed one by one for each channel, and a matrix containing only defect but no noise is obtained.

IV. EVALUATION METHOD OF FILTERING EFFECT

A. THE INDICATOR OF FILTER EFFECT EVALUATION

The adaptive canceller is applied to filter the multi-channel MFL signal. Before and after filtering, the information on defect is retained and the noise interference is suppressed. In this case, the quantitative analysis of the filtering effect plays a vitally important role in evaluating the filtering method.

Considering that the adaptive canceller removes the noise-related part of the noisy signal, the defect is preserved before and after filtering, while the noise intensity is weakened. In the meantime, the data is made up of long signals as the probability of rail damage is low. Among them, there are a small number of defective signals, which makes the noise relatively large when the signal-to-noise ratio is calculated. Consequently, the result of signal-to-noise ratio calculation is small, and the change to signal-to-noise ratio is unable to reflect the degree of noise percentage attenuation. In summary, the rate of change in pure noise energy is used before and after filtering as an indicator to evaluate the filtering effect, which is expressed as:

$$\eta = \frac{E_{n0} - E_{n1}}{E_{n0}} \tag{6}$$

where E_{n0} represents the original signal pure noise total power, E_{n1} indicates the pure noise total power of the filtered signal, and η denotes the rate of change in pure noise energy before and after filtering.

B. η FOR CALCULATING RAILS MFL SIGNALS

The data to be filtered is the leakage magnetic data on the known section of railway. Therefore, the position and number of the damage on the rails can be determined, and the position of the defect in the data can be calibrated, as a result of which what can be removed is only the defect in the data. With pure noise collected, the rate of change of pure noise energy is calculated before and after filtering according to formula (6), and the degree of noise suppression by the filtering method can be known. Fig. 7 shows the calculation process for the filter effect indicator:

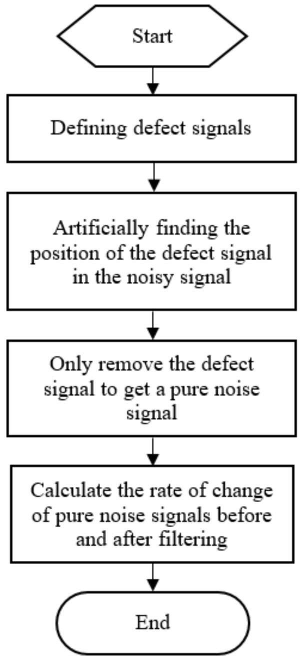


FIGURE 7. Flowchart of filter effect indicator calculation.

The length of data of the defect changes with the intensity of the signal. At the same time, the length of defect is defined as from the second zero left to the first zero right of the maximum point according to the characteristics of magnetic field distribution corresponding to the defect. The defect is shown in Fig. 8.

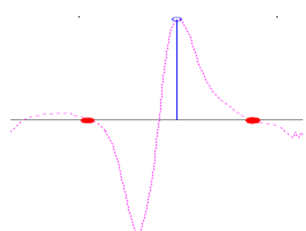


FIGURE 8. MFL signal of the defect.

V. RESULTS AND DISCUSSIONS

A. EXPERIMENTS AND RESULTS

At the speed of 30km/h, the Z-direction MFL signal of the measured rails with 8 pits is selected for signal processing. This data can reflect the complex vibrations occurring during MFL high-speed inspections and the defect in the Z-direction leakage magnetic field shows easy-to-view bimodal characteristic. The railway line consists of rail with artificial pit defects. As shown in Fig. 9, there are artificial defects found in the rail and MFL detecting probe. The calibration line of the artificial damage is shown in Fig. 10.

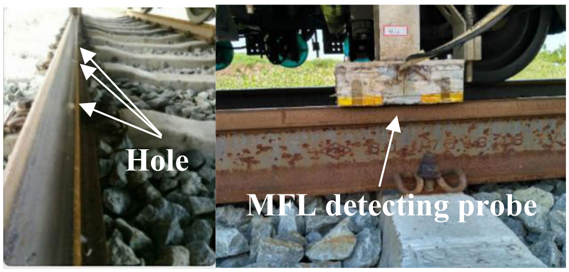


FIGURE 9. On-site rails and MFL detecting probe.

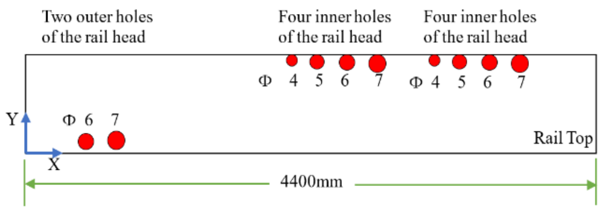


FIGURE 10. Artificial damage diagram.

In order to verify the rationality of the virtual channel and the filtering effect produced by the method, the correlation analysis is first performed on the virtual channel and the general channel in the absence of useful signal. Then, a comparison is performed in the MFL signals before and after the filtering. The filtering process and its effects are detailed as follows:

(1) The MFL signals of rail are collected by MFL detection system, and the original signal containing 13 signals are obtained. The single channel signal (green line) and the multi-channel signals as shown in Fig. 11 and 14(a), respectively. It can be seen from the figures that it is difficult to distinguish the defect from the vibration signal, so the adaptive filtering method is needed to process the data.

(2) The virtual channel construction algorithm is applied to obtain the virtual channel. As shown in Fig. 11, the virtual channel signal constructed by the algorithm is the red line in the figure. It can be seen from the figure that the virtual channel signal shows a low correlation or even no correlation with the defect in the place where the defect occurs. By contrast, it exhibits a close association with the noise in other places.

In order to analyze the correlation between virtual channels and other channels, their correlation coefficients are calculated according to Equation (7), as shown in Fig. 13. From Equation (4), it can be known that the closer the correlation between the reference signal and the noise in the noisy signal, the more satisfactory the adaptive filtering effect. The signal of the virtual channel is related to the signal of the 13 channels, where the correlation coefficient of the signal in channels 5∼11 exceeds 91%, followed by the signal in channels 1∼4 (85-90%) and the signal in channels 12∼13 (less than 80%). Since there are 10 holes distributed on both sides of the rail, the intermediate sensor is unable to detect the defect leakage magnetic field. The 13 signals are classified as follows. Channels 1∼4 collect two defects, channels 12∼13 collect up to eight defects, channels 5∼11 contain only interference signals. It can be seen that the signal of the virtual channel is closely correlated with the noise in the noisy

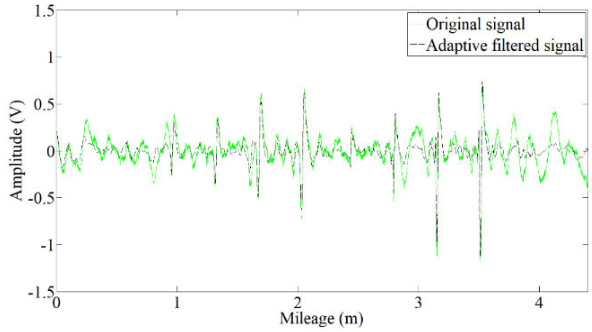


FIGURE 11. Contrast figure of the 13th channel MFL signal before and after filtering.

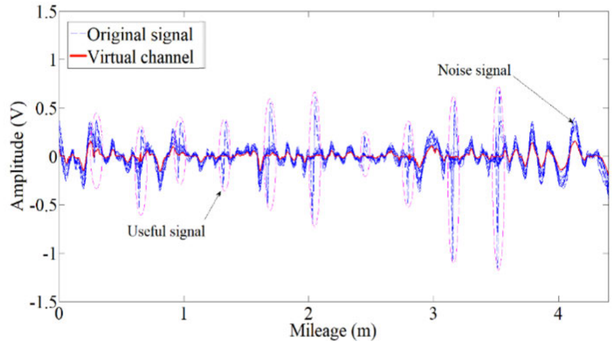


FIGURE 12. The relative position of virtual channel signal and multichannel signal.

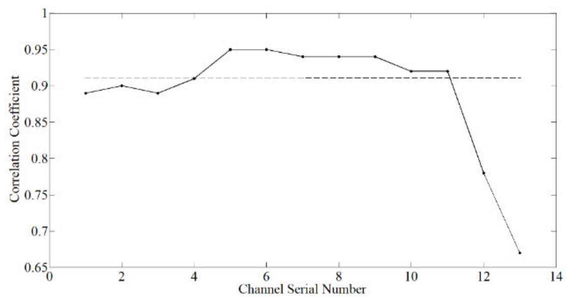


FIGURE 13. Correlation coefficients of virtual channels with other channels.

signal, suggesting that the signal of the virtual channel can be applied as a reference signal for the adaptive filter.

$$\rho x_i, x_0 = \frac{E\left(x_i x_0\right) - E\left(x_i\right)\left(x_0\right)}{\sqrt{E\left(x_i^2\right) - E^2(x_i)}\sqrt{E\left(x_0^2\right) - E^2(x_0)}} \quad (7)$$

(3) Based on the adaptive filtering algorithm, the virtual channel construction algorithm is applied to construct the adaptive noise canceller, and the rail leakage magnetic signal is filtered for a second time. With the virtual channel obtained above as the reference signal for the adaptive filter, single-channel filtering is performed one by one for each channel. Finally, the filtering of the entire MFL matrix $\tilde{X}$ is made relatively pure. The adaptive filtering algorithm is applied to perform the single-channel comparison before and after filtering, as shown in Fig. 11. The multi-channel comparison is shown in Fig. 14(b). It can be seen from these comparisons that the noise of the original signal is significantly weakened after the filtering method proposed in this paper is adopted. Moreover, the defect submerged by the noise is clearly observed. There are 10 defects distributed on both sides of the top surface of the rail.

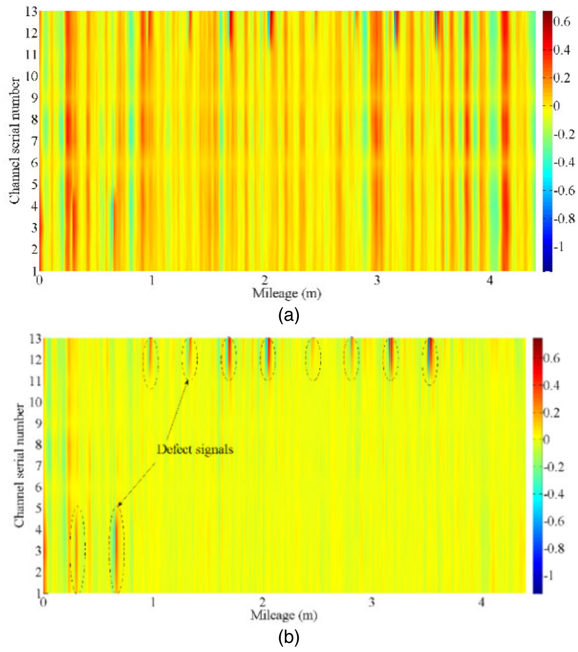


FIGURE 14. **All channel MFL signals: (a) The original signal before filtering; (b) The filtering result of the method in this paper.**

B. EVALUATION AND ANALYSIS OF FILTERING EFFECT

According to the method proposed above, the filtering effect achieved in this paper is evaluated with the 13th channel of detecting eight defects as an example.

First of all, the defect location is marked, as shown in Fig. 15. The purple line indicates the single-channel filtered data, and the blue line represents the location of the artificially marked defect. In Figures 16 to 18, the horizontal

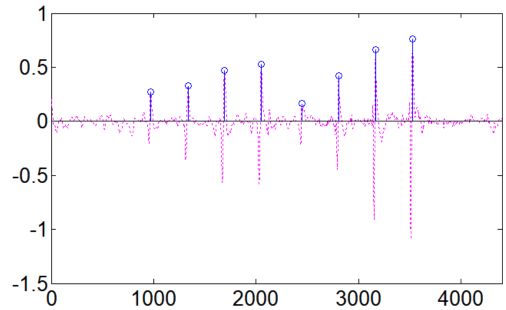


FIGURE 15. **Marking the defect.**

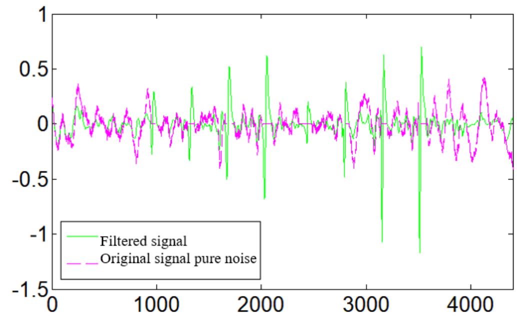


FIGURE 16. **Single channel pure noise signal before filtering.**

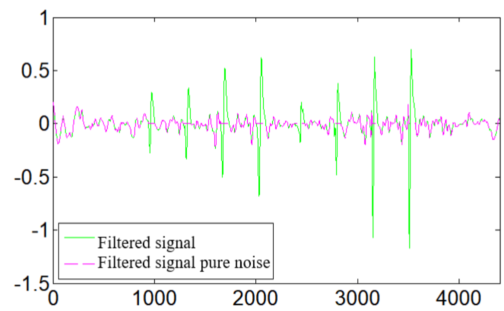


FIGURE 17. **Single channel pure noise signal after filtering.**

axis denotes the number of sampling points and the vertical axis indicates the voltage amplitude.

Then, the pure noise signals before and after filtering are obtained, respectively. Fig. 16 shows the single channel pure noise signal before filtering, while Fig. 17 shows the single channel pure noise signal after filtering. In Figures16 and 17, the purple line indicates pure noise signal and the green line denotes filtered signal.

Finally, the rate of change in pure noise energy before and after the 13th channel filtering is 81.44%, which means that the adaptive filtering method reduces the noise intensity by 81.44%. It is thus indicated that the filtering effect is significant.

C. ANALYSIS OF THE APPROPRIATENESS OF THE FILTERING METHOD

In order to demonstrate the capability of generalization achieved by this filtering algorithm, the experimental data

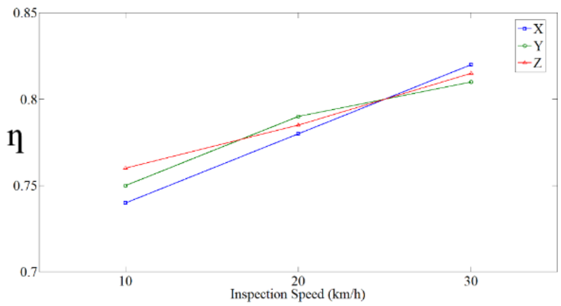


FIGURE 18. η at different speeds and directions.

of different speeds and directions are selected to filter and calculate the filtering effect, as shown in Fig. 18.

It can be seen from the figure that the noise intensity of MFL signals at different speeds and sensor directions (X, Y and Z directions) is reduced by 74%∼82%. As shown in Fig. 18, the filtering effect is made more significant by the increase of speed, which is because the η decreases as speed is on the rise. Also, it can be known that the filtering method proposed in this paper shows a more significant advantage in processing high-speed MFL signals.

VI. CONCLUSION AND FUTURE WORK

In this paper, an improved adaptive filtering method is proposed, to reduce the interferences caused by vibration in the high-speed inspection process by more than 80%, which indicates the significant filtering effect. According to the analysis, the noise in the rail leakage magnetic high-speed inspection system is vibration interference, and it shows similarity to the power spectrum overlap of the defect. Firstly, based on the analysis conducted of the relationship between the noise and the defect in the high-speed MFL detection process, combined with the characteristics of the array sensor signal, the virtual channel with the similarity of the actual channel without the defect exceeds 90%. Additionally, an adaptive reference canceller is constructed to filter the high-speed MFL detection signal. Then, in order for quantitative evaluation of the filtering effect, the energy change rate of the noisy signal with the useful signal before and after filtering is proposed as an index for the evaluation of the filtering effect. In the meantime, to verify the generalization ability of the algorithm, the algorithm is applied at different speeds and directions. According to the results, the noise intensity remains above 74%, and the filtering effect is made more significant with the increase of speed, which is conducive to addressing the filtering problem with high-speed MFL detection signal. The adaptive filtering method of the MFL signal on the top surface of the rail makes the defect easy to observe, which plays a significant role in improving the detection rate of the rail top surface defect and facilitating the subsequent quantitative analysis or state reconstruction.

The improved adaptive filtering method proposed in this paper is verified as reasonable only when two preconditions are satisfied. One is that the defects whose directions are parallel to the rail joint and whose length is the same as the width of the rail will be filtered out as noise. The other is that the signals of all channels are filtered by the same reference signal. To improve the filtering effect, it is necessary to consider the spatial difference between the sensors. Therefore, the future work will be focused on finding a way to obtain the optimal reference signal for each channel. In doing so, each channel can produce the best possible filtering effect.

REFERENCES

[1] W. Ze-song, "Research on image detection and recognition for defects on the surface of the steel plate based on magnetic flux leakage signals," in *Proc. 29th Chin. Control Decis. Conf. (CCDC)*, Chongqing, China, May 2017, pp. 6139–6144.

[2] Z. Yang, B. Anthonie, and R. Chen, "Numerical and experimental study of wheel-rail impact vibration and noise generated at an insulated rail joint," *Int. J. Impact Eng.*, vol. 113, no. 11, pp. 29–39, Mar. 2018.

[3] E. P. Dudkin, L. A. Andreeva, and N. N. Sultanov, "Methods of noise and vibration protection on urban rail transport," *Procedia Eng.*, vol. 189, no. 5, pp. 829–835, Dec. 2017.

[4] B. Y. Mao, Y. Lu, and P. L. Wu, "Signal processing and defect analysis of pipeline inspection applying magnetic flux leakage methods," *Intell. Service Robot.*, vol. 7, no. 4, pp. 203–209, Oct. 2014.

[5] J. Daniel, R. Mohanagayathri, and A. Abudhahir, "Characterization of defects in MFL images using wavelet transform and neural network," in *Proc. 21th Int. Conf. Electron. Commun. Sys.*, Coimbatore, India, Feb. 2014, pp. 13–14.

[6] K. Erazo, D. Sen, S. Nagarajaiah, and L. Sun, "Vibration-based structural health monitoring under changing environmental conditions using Kalman filtering," *Mech. Syst. Signal Process.*, vol. 117, pp. 1–15, Feb. 2019.

[7] E. Fotiadou, J. O. E. H. van Laar, S. G. Oei, and R. Vullings, "Enhancement of low-quality fetal electrocardiogram based on time-sequenced adaptive filtering," *Med. Biol. Eng. Comput.*, vol. 56, no. 12, pp. 2313–2323, Dec. 2018.

[8] L.-M. Bai, M.-H. Fan, C.-H. Feng, and L.-H. Wang, "Using an adaptive filter to remove ECG motion artifact interference," in *Proc. IEEE Int. Conf. Consum. Electron.-Taiwan (ICCE-TW)*, Taichung, Taiwan, May 2018, pp. 40–44.

[9] B. Liu, L. Y. He, H. Zhang, Y. Cao, and H. Fernandes, "The axial crack testing model for long distance oil-gas pipeline based on magnetic flux leakage internal inspection method," *Measurement*, vol. 103, no. 2, pp. 275–282, Jun. 2017.

[10] T. Zhang, G. Tian, and X. Zuo, "Pulsed magnetic flux leakage sensor systems and applications," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf.*, Hangzhou, China, May 2011, pp. 1–6.

[11] G. Piao, J. Guo, T. Hu, H. Leung, and Y. Deng, "Fast reconstruction of 3-D defect profile from MFL signals using key physics-based parameters and SVM," *NDT E Int.*, vol. 103, pp. 26–38, Apr. 2019.

[12] H. Zhu and W. Liu, "Magnetic flux leakage nondestructive testing technology of high-speed rail defects," in *Proc. 4th Int. Conf. Sensors, Mechatronics Autom. (ICSMA)*, Zhuhai, China, 2016, pp. 438–441.

[13] R. Sanchís, S. Cardona, and J. Martínez, "Determination of the vertical vibration of a ballasted railway track to be used in the experimental detection of wheel flats in metropolitan railways," *J. Vib. Acoust.*, vol. 141, no. 2, pp. 1–16, Apr. 2019.

[14] G.-J. Li, J. Zhang, and C. Li, "Signal process technology of train vibration," in *Proc. 35th Chin. Control Conf. (CCC)*, Chengdu, China, Jul. 2016, pp. 10187–10192.

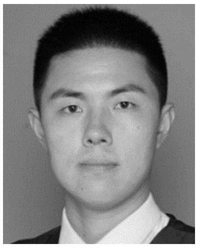
[15] A. El Kacimi, P. K. Woodward, O. Laghrouche, and G. Medero, "Time domain 3D finite element modelling of train-induced vibration at high speed," *Comput. Struct.*, vol. 118, pp. 66–73, Mar. 2013.

[16] E. Eweda, "Stabilization of high-order stochastic gradient adaptive filtering algorithms," *IEEE Trans. Signal Process.*, vol. 65, no. 15, pp. 3948–3959, Aug. 2017.

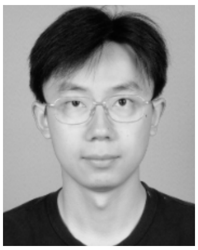
[17] S. B. S. Fareed and S. S. Khader, "Fast adaptive and selective mean filter for the removal of high-density salt and pepper noise," *IET Image Process.*, vol. 12, no. 8, pp. 1378–1387, Aug. 2018.

[18] A. S. Douglass and D. R. Dowling, "Compressive spectral estimation methods using a noise reference," *J. Acoust. Soc. Amer.*, vol. 142, no. 4, p. 2555, Oct. 2017.

[19] O. Zhang and X. Y. Wei, "Analysis of MFL model for sucker rod defects and its MFL signal processing," *J. Test. Eval.*, vol. 47, no. 5, p. 687, Sep. 2019.
[20] J. R. Mohammed, "Development of two-input adaptive noise canceller for wideband and narrowband noise signals," *Int. J. Speech Technol.*, vol. 20, no. 3, pp. 741–751, Sep. 2017.
[21] M. N. Salman, P. T. Rao, and M. Z. Rahman, "Adaptive noise cancellers for cardiac signal enhancement for IOT based health care systems," *J. Theor. Appl. Inf. Technol.*, vol. 95, no. 10, pp. 2206–2213, May 2017.

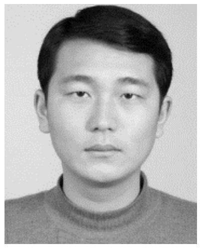


KAILUN JI received the B.Eng. and M.S. degrees in techniques and instruments of measurement from the Nanjing University of Aeronautics and Astronautics, China, in 2016 and 2020, respectively, where he is currently pursuing the Ph.D. degree. His research interests include nondestructive testing, signal processing, and system modeling.

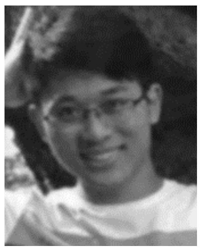


PING WANG received the Ph.D. degree in techniques and instruments of measurement from Southeast University, China, in 2004. From 2004 to 2007, he was a Postdoctoral Research Fellow with the Department of Radio Engineering, Information Security Research Center, Southeast University. He is currently a Professor with the Nanjing University of Aeronautics and Astronautics, China. His research interests include nondestructive testing, blind signal processing, and neural networks.

YINLIANG JIA received the M.S. and Ph.D. degrees in techniques and instruments of measurement from the Nanjing University of Aeronautics and Astronautics, China, in 2007 and 2011, respectively. From 2011 to 2020, he was with the Nanjing University of Aeronautics and Astronautics, as a Lecturer. He has authored over ten refereed articles. His research interests include electromagnetic nondestructive testing and signal processing.



YUNFEI YE received the dual Ph.D. degree in techniques and instruments of measurement from the Nanjing University of Aeronautics and Astronautics, China, in 2014 and 2018, respectively. Since 2018, he has been with the Nanjing Institute of Railway Technology, China, as an Associate Professor. He has authored over 18 refereed articles. His research interest includes intelligent detection technology.



SHUNYI DING received the B.Eng. degree in engineering from Henan Polytechnic University, in 2017, and the M.S. degree in precision instrument from the Nanjing University of Aeronautics and Astronautics, in 2020. His research interests include nondestructive testing and blind signal processing.