

Enhanced ACFM detection performance by multi-parameter synergy analysis

Junqi Gao, Lingsi Sun, Shuxiang Zhao and Ying Shen

A procedure for the enhancement of alternating current field measurement (ACFM) detection performance is proposed based on a multi-parameter synergy analysis (MPSA) algorithm. Firstly, to gain the maximised ACFM signal characteristics, wavelet base property matching is adopted to choose the favourable wavelet bases. To this aim, the following six base properties should be considered: orthogonality, compact support, symmetry, discrete wavelet transform (DWT), vanishing moment and regularity. It is found that the applicable wavelet bases are Haar, Daubechies (DbN), Symlets (SymN) and Coiflets (CoifN). Secondly, the MPSA method is applied to select the optimal mother wavelet candidates. The candidate with the largest MPSA index value is regarded as the optimum wavelet base. Finally, the proposed MPSA denoising strategy is demonstrated using an ACFM experiment. The results indicate that wavelets Db4 with decomposition level (DL)9 and Sym7 with DL8 are most appropriate for x- and z-axis ACFM signal denoising, respectively. The enhanced ACFM detection performance is experimentally verified and it is found that the signal-to-noise ratio (SNR) is increased by 33.8 dB and 26.7 dB for the x- and z-axis signal, respectively.

Keywords: ACFM signal, wavelet denoising, wavelet base, multi-parameter synergy analysis.

1. Introduction

Alternating current field measurement (ACFM) is a widely-used non-destructive testing (NDT) technology that has been developed in recent years. It can produce a uniform electromagnetic field and a magnetic anomaly detection field due to defects in safety-critical structures, such as the oil & gas, aeronautical and railway industries^[1,2]. Such perturbation of the magnetic field is measured to identify the size of the target defects in terms of depth and length^[3]. An ACFM inducer is needed to apply the current on the surface of a specimen. It has been suggested that the U-shaped inducer is promising in exhibiting excellent induction properties^[4], where the optimal lift-off value and excitation frequency are reported to be 4 mm and 6 kHz, respectively^[5,6]. Many effective methods have been proposed as a result of the identification of these key parameters, such as a two-step interpolation algorithm based on circumferential current field testing^[2], a fuzzy learning approach for the identification of arbitrary cracks^[7] and rotating ACFM^[8].

Reliable signal processing methods are indispensable for the extraction of ACFM signal characteristics, which are invariably contaminated by noise nuisance. The challenge of filtering out the noise from the real signal to obtain useful information has restricted the extensive applications of the ACFM technique. Though time-frequency analysis methods have been used for ACFM signal processing, wavelet threshold denoising is still preferred and has been demonstrated with better processing accuracy^[9,10]. However, the denoising effects of different wavelet bases are variable even when analysing the same signal^[11].

Finding the most appropriate mother wavelet is the main aim in many wavelet selection procedures. Wang *et al*^[12] studied wavelet base selection in the acoustic emission signals of the concrete damage process by calculating the energy entropy. Baili *et al*^[13] analysed the denoising approach by discrete wavelet transform for ground-penetrating radar signals. Garg^[14] addressed the problem of mother wavelet selection for wavelet signal processing in feature extraction and pattern recognition. The signal-to-noise ratio (SNR) and the

● Submitted 19.09.19 / Accepted 18.12.19

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normalised root-mean-square error were considered to evaluate the performance of wavelet denoising. Wijaya *et al*^[15] proposed an information quality ratio as a novel metric for mother wavelet selection of electronic noise signals in beef quality classification. Performance comparisons of various decomposition levels have been studied in previous reports. Gavrovska *et al*^[16] derived the best choice of wavelet decomposition levels from PhysioNet’s datasets for cardio signal filtering. Srivastava *et al*^[17] presented a new wavelet shrinkage method for selecting decomposition levels and noise thresholds. Yang *et al*^[18] discussed the choice of decomposition levels for wavelet-based hydrological time-series modelling. Pradhan *et al*^[19] attempted to determine the optimal number of decomposition levels for wavelet-based fusion, which yields the optimal spatial and spectral quality. Previous studies have indicated that appropriate selection of the mother wavelet family can contribute to the denoising performance in many aspects, for example in terms of smoothness, computational load and the reservation of detailed signal characteristics.

Typically, for the mother wavelet family selection, four standard metrics should be taken into account, which are correlation coefficients (CC), signal-to-noise ratio (SNR), mean square error (MSE) and flatness (F)^[12,20]. CC describes the similarity between the theoretical signal and the denoised signal and the value is positively correlated with the denoising effect. SNR represents the influence of the presence of noise on the overall signal. MSE is a parameter relating to the difference between the original signal and the denoised signal, which reflects the overall error of the denoised signal. F is the only factor that emphasises the low-frequency approximation information of the signal, which is used as a cue for local variability. The overall features of the original signal can be evaluated by CC, SNR and MSE, while F serves to assess the detailed characteristics of the signal; thus, the local bias of the signal can be revealed. To choose an optimal wavelet family, the traditional method depends on evaluating one or some of the selecting criteria. However, it is likely to result in poor performance in other metrics not chosen and, consequently, essential signal characteristics may be lost.

In this study, to solve the problem, a multi-parameter synergy analysis (MPSA) method is employed to evaluate the effects of a denoised signal with respect to different wavelet bases by taking the comprehensive criteria into consideration. MPSA is the sum of the four evaluating metrics that are weighed by an algorithm. The mother wavelet, having the maximum MPSA value, suggests the best ACFM detection performance, which is clear when increasing the SNR by 33.8 dB and 26.7 dB for the *x*- and *z*-axis signal, respectively.

2. Method

The main principle of wavelet denoising rests on the strong correlation of the wavelet. If the selected wavelet base is similar to the original signal, it tends to result in a large wavelet coefficient. It is known that wavelet coefficients with large amplitude values are mostly made up of signal, whereas those with small amplitude values are largely made up of noise. Noise energy after wavelet transform does not have concentrated characteristics due to the absence of the correlation of wavelets. Indeed, choosing the optimal mother wavelet is perhaps the most difficult technical obstacle in ACFM signal denoising.

The technique described for ACFM noise reduction starts with wavelet base property matching. To choose the qualified wavelet bases, some fundamental base properties should be included, such as orthogonality, compact support, symmetry, continuous wavelet transform (CWT), discrete wavelet transform (DWT), vanishing moment and regularity^[21]. Available popular mother wavelets are summarised in Table 1, which are characterised by the above-mentioned base properties^[12].

In practical application, the collection of ACFM signals is time consuming and the large amount of data obtained incurs heavy computational burden. Compared with CWT, DWT requires lower levels of computation, which is favourable for ACFM signal computing. It should be noted that the ACFM signal is a transient response to a minute crack. Thus, a wavelet base with compact support is necessary to identify the ACFM signal accurately in both the time and frequency domains. As the width of the compact support is narrow, it can embody rich instantaneous characteristics of the time-domain signal and allow instant large-scale data computation. Moreover, the base property of regularity governs the local quality of the frequency-domain signal, which can make abundant and smooth graphic detail after signal reconstruction. However, the increased regularity will produce a wider support width and poorer local signal quality, resulting in a heavy calculation load. Thus, a trade-off should be taken between the base properties of regularity and compact support. Typically, the vanishing moment property is related to the singularity of the signal, which is desirable to distinguish the ACFM signal from the background noise. Finally, the wavelet bases with the properties of orthogonality and symmetry are required to process the ACFM signals because orthogonality is a reflection of the integrity of the wavelet base, which indicates the redundancy of the signal. The good orthogonal property is beneficial for accurate signal reconstruction after denoising. The property of symmetry determines whether the wavelet filter has a

Table 1. The properties of available popular wavelet bases

Wavelet base	Property						
	Orthogonality	Compact support	Symmetry	CWT	DWT	Vanishing moment	Regularity
Morlet	×	×	✓	✓	×	–	×
Mexican hat	×	×	✓	✓	×	–	×
Meyer	✓	×	✓	✓	✓	–	✓
BiorNr-Nd	×	✓	Approximately	✓	✓	Nr-1	×
Haar (Db1)	✓	✓	✓	✓	✓	1	✓
Daubechies (DbN)	✓	✓	Approximately	✓	✓	N	✓
Symlets (SymN)	✓	✓	Approximately	✓	✓	N	✓
Coiflets (CoifN)	✓	✓	Approximately	✓	✓	2N	✓

linear phase, which can avoid signal distortion during the processes of signal decomposition and reconstruction. Therefore, the key base properties that are indispensable for ACFM signal wavelet transformation are DWT, compact support, symmetry, regularity, orthogonality and certain vanishing moment. Therefore, according to Table 1, the qualified wavelet bases for ACFM are Haar, Daubechies, Symlets and Coiflets. It should be noted that when the order N is equal to one, Haar is the same as Db1.

In addition to wavelet base screening, the decomposition level should be emphasised during the denoising process, which could improve the denoising efficiency equally^[16]. A high decomposition level is able to eliminate more noise. However, signal distortion could occur if the decomposition level is set too high. To avoid this issue, wavelet decompositions levels are limited in this work, which is demonstrated experimentally in detail in Section 3.

A coefficient of variation algorithm is used to weigh each assessment factor. The coefficient of variation of each assessment factor is given as^[22]:

$$M_{Ki} = \frac{\sigma_{Ki}}{\mu_{Ki}} \quad i = 1, 2, 3, 4 \dots \dots \dots (1)$$

where σ is the standard deviation of each factor value, μ is the average value of each factor and K_1 , K_2 , K_3 and K_4 represent the factors of CC, SNR, MSE and F, respectively. Then, the weight of each indicator can be defined as:

$$W_{Ki} = \frac{M_{Ki}}{\sum_{i=1}^4 M_{Ki}} \dots \dots \dots (2)$$

The normalised value V is obtained by the min-max normalisation algorithm for the four parameters using Equations (3)-(6):

$$V_{CC,j} = \frac{CC_j - \min(CC)}{\max(CC) - \min(CC)} \quad j = 1, \dots, n \dots \dots \dots (3)$$

$$V_{SNR,j} = \frac{SNR_j - \min(SNR)}{\max(SNR) - \min(SNR)} \quad j = 1, \dots, n \dots \dots \dots (4)$$

$$V_{MSE,j} = \frac{\max(MSE) - MSE_j}{\max(MSE) - \min(MSE)} \quad j = 1, \dots, n \dots \dots \dots (5)$$

$$V_{F,j} = \frac{\max(F) - F_j}{\max(F) - \min(F)} \quad j = 1, \dots, n \dots \dots \dots (6)$$

where CC_j , SNR_j , MSE_j and F_j represent the datasets before normalising and n represents the total amount of the conditions with different wavelet bases and decomposition levels. The MPSA index for each wavelet base can be expressed as:

$$MPSA_j = \sum_{i=1}^4 W_{Ki} \times V_{Ki,j} \quad j = 1, \dots, n \dots \dots \dots (7)$$

Finally, the optimised wavelet base is selected based on the MPSA index. The higher value of MPSA implies better denoising performance without loss of any essential information and the original signal characteristic.

Figure 1 features a block diagram showing the ACFM performance improvement method. Firstly, property matching is applied to select the appropriate wavelet bases with the aim of maximising ACFM signal characteristics. The applicable wavelet bases, which should have the properties of orthogonality, compact support, symmetry, DWT, vanishing moment and regularity, are Haar, Daubechies, Symlets and Coiflets. Then, the selected wavelet bases are examined using the MPSA evaluation method to identify the optimal one based on the coefficient of variation and the

min-max normalisation algorithm. The wavelet base that has the largest MPSA value is chosen as the most suitable for ACFM signal denoising.

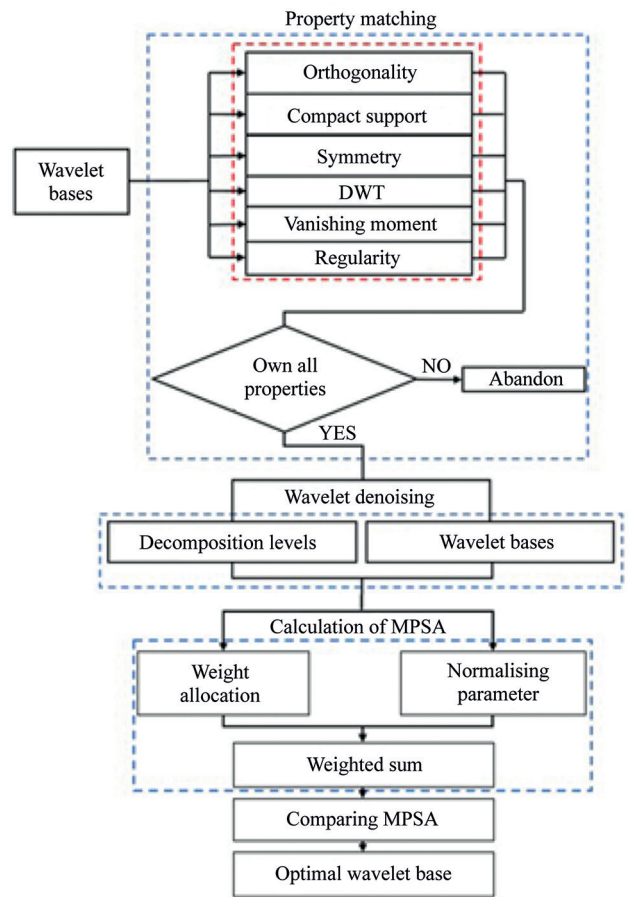


Figure 1. Block diagram showing ACFM denoising based on property matching and MPSA evaluation

3. Experiment and results

The system set-up is illustrated in Figure 2 and comprises a tunnel-magneto-resistance (TMR) sensor mounted on a U-shaped inducer. The analogue output signal from the sensor is sent to a data logger (USB-6210, National Instruments, USA). The U-shaped inducer is powered by a functional generator (AFG1022, Tektronix, USA) at an excitation voltage of 2 V and a frequency of 3 kHz. The TMR sensor that can move with the inducer equally is driven by a DC power supplier (E36311A, Keysight, USA). The length and depth of the 0.6 mm-wide crack are set at 40 mm and 6 mm, respectively. The obtained B_x and B_z ACFM signals are shown in

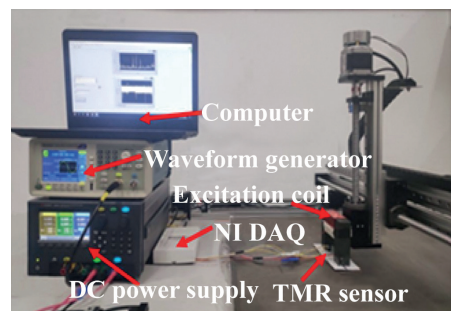


Figure 2. Experimental set-up

Figures 3(a) and 3(b), respectively. It can be seen that the interference noise is superimposed over the real signal, leaving ambiguity in pinpointing the critical points on the curves. Thus, it poses a difficult challenge for engineers to estimate the crack size correctly before applying a noise reduction procedure.

Figures 4 and 5 show the MPSA diagrams in terms of three wavelet bases, DbN, CoifN and SymN, and under nine different decomposition levels for x - and z -axis ACFM signals, respectively. It can be seen that the performances of wavelet bases Sym1 and Db1 at level 3 decomposition are worse than the others. Here, only the wavelet decomposition level limited within nine levels is discussed, because higher levels of decomposition suffer from unfavourable signal distortion and loss.

To find the optimal wavelet base, MPSA values of decomposition levels 7, 8 and 9 are summarised in Table 2. For the x -axis ACFM signal, it can be seen that the Db4 wavelet base with level 9 decomposition reaches the highest MPSA value of 0.985213 and can be considered as the optimal base for the x -direction ACFM signal. The Sym7 wavelet base with level 8 decomposition is considered as the optimal base for the z -direction ACFM signal, as it reaches the largest MPSA value of 0.979604.

Then, the x - and z -axis signal denoised by the chosen wavelet base of Db4 and Sym7 is illustrated in Figures 6(a) and 6(b), respectively. The Figures show that this wavelet transform approach offers a good denoising effect, where ACFM fingerprint characteristics can be well extracted and interpreted. The SNR is increased by 33.8 dB and 26.7 dB for the x - and z -axis signal, respectively. In Figure 6(a), the crack depth can be quantified according to the variance in B_x magnitudes between background (point A or B) and minimum (point C) levels. In Figure 6(b), the value of B_z can be clearly seen to have a peak at point D and a trough at point E, respectively. The distance along the x -axis between points D and E is measured at 38.51 mm, which is an indicator of the crack length of 40 mm. Therefore, these experiments provide direct evidence for the feasibility of the proposed MPSA method to improve ACFM detection performance.

4. Conclusion

In this work, an MPSA method is presented to improve ACFM detection performance. The proposed MPSA algorithm rests on comprehensive consideration of the four standard metrics, which are CC, SNR, MSE and F. The experimental results demonstrate that wavelet bases Db4 at level 9 decomposition and Sym7 at level 8 decomposition are the most desirable candidates for processing the x - and z -axis of ACFM signals, respectively. Based on the selected optimal wavelet base, future work will be devoted to examining if such a denoising strategy is capable of eliminating the background noise incurred by weld roughness. The authors believe that such a technique is promising in applying wavelet transform for ACFM signal denoising and further interpretation.

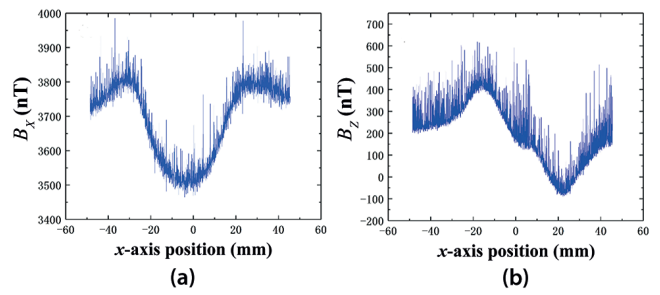


Figure 3. The original ACFM signal along: (a) the x -direction; and (b) the z -direction

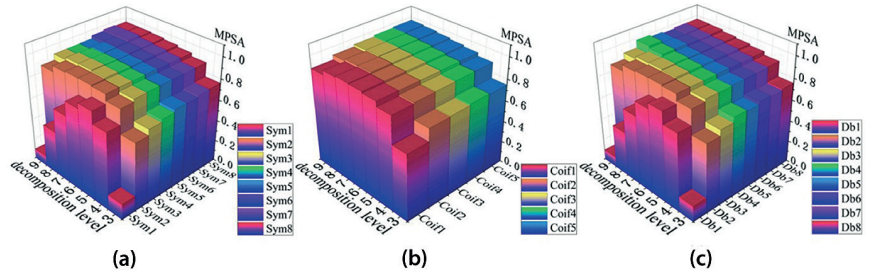


Figure 4. MPSA diagrams of the ACFM signal along the x -direction for three wavelet bases: (a) SymN; (b) CoifN; and (c) DbN

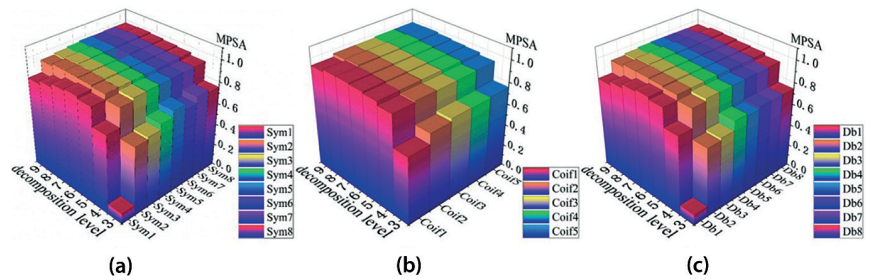


Figure 5. MPSA diagrams of the ACFM signal along the z -direction for three wavelet bases: (a) SymN; (b) CoifN; and (c) DbN

Table 2. MPSA values of decomposition levels 7, 8 and 9

Wavelet base	x -direction			z -direction		
	Level 7	Level 8	Level 9	Level 7	Level 8	Level 9
Db4	0.949623	0.966236	0.985213	0.966679	0.97628	0.959053
Db8	0.949259	0.964288	0.967428	0.966891	0.974576	0.959866
Sym5	0.939697	0.947011	0.92214	0.882656	0.973617	0.971365
Sym7	0.948669	0.965561	0.962638	0.965635	0.979604	0.9729
Coif5	0.950795	0.961725	0.969208	0.968305	0.979172	0.975752

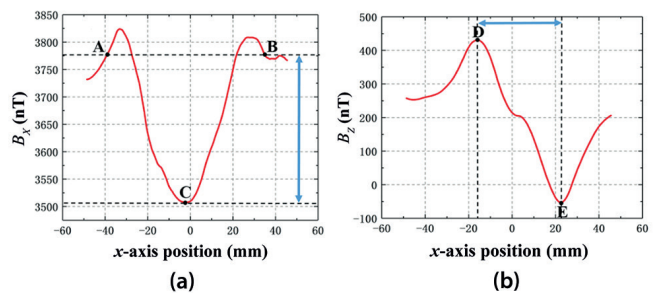


Figure 6. (a) Denoised x -axis B_x signal under wavelet base of Db4; and (b) denoised x -axis B_z signal under wavelet base of Sym7

Acknowledgements

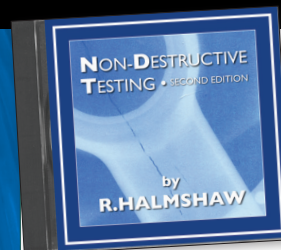
This work was supported by the Natural Science Foundation of Heilongjiang Province (LH2019E040) and the Academy of Space Electronic Information Technology (6142411183410). The project was also supported by China Ship Development and Design Center grant KY10500190043 and Acoustic Science and Technology Laboratory grant JCKYS2019604SSJS005.

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