Chapter 8
Mitigating Speckle Noise while Preserving Impact Response in Vibration Measurements with Laser Doppler Vibrometer on a Moving Platform

Yuanchen Zeng, Alfredo Núñez, and Zili Li

Abstract Laser Doppler Vibrometer measures structural vibrations contactlessly. By using a laser Doppler Vibrometer on a moving platform (LDVom), the vibration of a structure can be measured continuously along a specific path, covering all points on the path in a single scan. Impact responses are prevalent in structural vibrations and useful for modal analysis and structural health monitoring. However, speckle noise can significantly degrade the quality of LDVom signals, so it is essential to remove speckle noise while preserving structural vibrations, including impact responses. However, both impact response and speckle noise are impulsive and transient in the time domain and broadband in the frequency domain, making it difficult to distinguish them and treat them differently in signal processing. To address this challenge, this paper develops a novel denoising method to mitigate speckle noise while preserving impact response in LDVom signals. Instead of directly detecting speckle noise, the proposed method is inspired by conventional wavelet denoising that works in an orthogonal domain but introduces key differences tailored to address the unique properties of speckle noise. Wavelets with shapes similar to speckle noise are utilized, and the strategy of manipulating approximation and detail coefficients based on local noise intensity is proposed. Then, the developed method is validated through vibration measurements in two cases – one with artificial excitations and the other with operational excitations. In the former case, a full-scale slab track sample subjected to manual impact excitations is measured by an LDVom. In the latter case, the rail of the TU Delft V-Track test rig subjected to a moving wheel load over a rail joint is measured by an LDVom. Different scanning speeds are tested in both cases, and the impact responses extracted from the LDVom signals are compared with signals measured by accelerometers mounted on the target structures. The results demonstrate the effectiveness and robustness of the developed method in mitigating speckle noise and preserving impact responses in the LDVom signals measured under different conditions and at different speeds.

Keywords Laser Doppler Vibrometer · Speckle Noise · Impact Response · Wavelet Denoising · Vibration Measurement

Introduction

Laser Doppler Vibrometer (LDV) is widely used for vibration measurements across various fields due to its non-contact nature, broad frequency band, and high sensitivity [1]. In most applications, an LDV remains static with respect to its target structure, such as fixed-point LDV [2], stepped-scanning LDV [3], and continuous-scanning LDV [4]. In contrast, a novel setup is to mount an LDV on a moving platform that moves with respect to the target structure, referred to as LDVom. This setup enables the vibration of a structure to be measured continuously along open paths. A typical example of LDVom is scanning transportation infrastructures using LDVs on a moving vehicle [5]∼[8].

In structural vibration measurements, capturing responses to impact loads is of significant interest because they carry the structural dynamics over a wide frequency range and are useful for modal analysis [9], fault diagnosis [10], and structural health monitoring [11]. Impact responses are typically transient in the time domain and broadband in the frequency domain. However, utilizing LDVom to capture such responses introduces a significant challenge – speckle noise. Speckle noise, caused by the change of interference patterns as a laser spot scans a rough surface [12], can significantly degrade the quality

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of LDVom signals. This challenge is usually addressed through specialized post-processing denoising methods. In [13], speckle noise is detected using the segment kurtosis ratio and then replaced with linear prediction. In [6] and [7], speckle noise is detected by a combination of Hampel identifier and stationary wavelet packet transformation clustering and then replaced through interpolation and smoothing. In [8] and [14], speckle noise is detected based on discrete wavelet transform, replaced with time series models, and then smoothed.

In summary, most existing denoising methods rely on the impulsive nature of speckle noise to detect and replace it in LDVom signals. However, impact responses also exhibit impulsive, transient, and broadband behaviors, making it difficult to distinguish between speckle noise and impact responses. This can lead to denoising errors, including impact responses being mistakenly treated as speckle noise or speckle noise not being fully detected and mitigated.

This paper aims to develop a novel denoising method that can effectively mitigate speckle noise in LDVom signals containing impact responses. Instead of directly detecting speckle noise, the proposed method decomposes an LDVom signal, manipulates the decomposition coefficients, and reconstructs the signal. The motivations behind and details of this method are presented in the Background and Methodology sections, respectively. The developed method is then validated experimentally through vibration measurements using LDVom in two cases – one with artificial excitations and the other with operational excitations. Comparisons are made with accelerometer measurements as well as the denoising results of two existing methods. These results are presented in the Validation Case 1 and Validation Case 2 sections.

Background

The developed method utilizes discrete wavelet transform (DWT), which allows for the separation and manipulation of different signal components in an orthogonal domain [15]. DWT also enables specific dynamic behaviors to be captured using wavelets that have similar shapes to these behaviors [16]. Conventional wavelet denoising generally consists of three steps: **1) decomposing** an original signal using DWT, **2) manipulating** the wavelet coefficients through thresholding, and **3) reconstructing** the signal by performing inverse DWT to the manipulated wavelet coefficients.

In cascade DWT, the raw signal is first decomposed (called level 1), and the approximation coefficient of the last level is decomposed from the second decomposition (called level 2). At each decomposition level, the approximation coefficients carry the main trend (low-frequency components) of the decomposed signal, while the detail coefficients carry the local feature (high-frequency components). Conventional wavelet denoising mainly aims to remove Gaussian white noise [17], so both approximation coefficients and large-magnitude detail coefficients are retained to preserve key features, whereas small-magnitude detail coefficients are removed or suppressed to filter out Gaussian white noise [17][18]. A variety of thresholding strategies have been developed, such as hard thresholding, soft thresholding, and universal threshold selection [19].

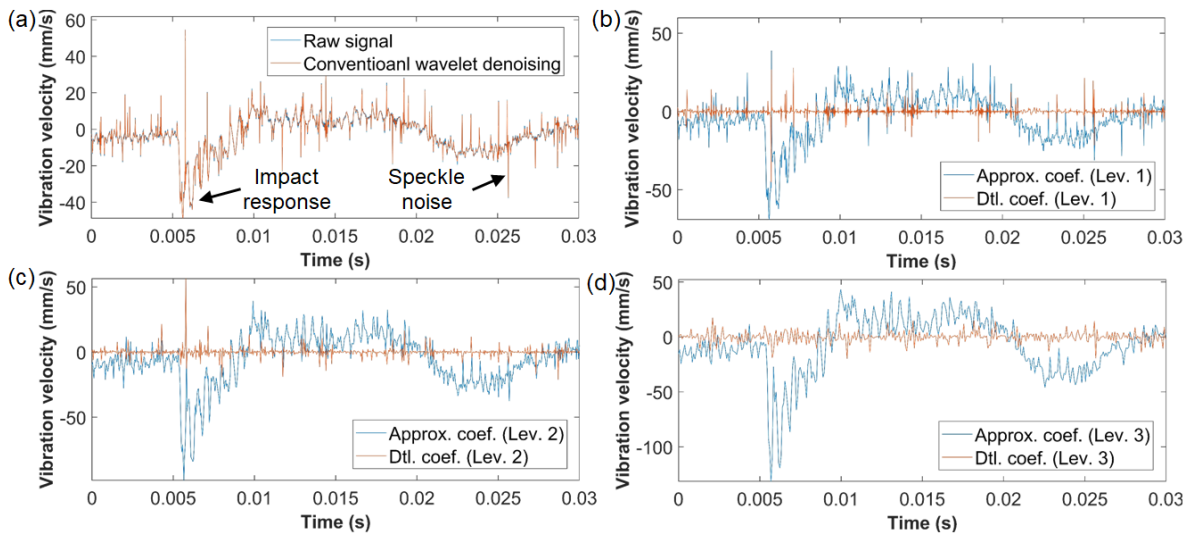

Fig. 1 Conventional wavelet denoising and decomposition results of an LDVom signal. (a) Raw and denoised signals; (b) wavelet coefficients at level 1; (c) wavelet coefficients at level 2; (d) wavelet coefficients at level 3.

However, conventional wavelet denoising has been found to be ineffective in preserving sharp features [17][19]. It has

also been reported in [20] that the wavelet denoising fails to remove spikes. These problems reduce the effectiveness of wavelet denoising in mitigating speckle noise while preserving impact responses in LDVom signals. For example, Fig. 1 (a) shows a measured LDVom signal and the result of conventional wavelet denoising. The impact response starts from approximately 5 ms, and speckle noise can be observed throughout the signal. Speckle noise still persists despite using a denoising level of 12 with a Symlet wavelet. The wavelet decomposition results in Fig. 1 (b)∼(d) reveal that at each level, the detail coefficient peaks at locations of speckle noise. However, conventional wavelet denoising removes only detail coefficients that are small, leaving speckle noise mostly unaddressed. Moreover, though the detail coefficients indicate the presence of the speckle noise, DWT cannot directly isolate the speckle noise and impact response into different wavelet coefficients: The approximation coefficients carry the impact response, but they are also affected by speckle noise; The detail coefficients at level 3 are also affected by the impact response, and the amplitude of the approximation coefficients is enlarged accordingly.

Methodology

The above analysis shows that speckle noise affects both detail and approximation coefficients in cascade DWT and conventional wavelet denoising is unsuitable for separating speckle noise in LDVom signals. To overcome this limitation, we develop a new wavelet denoising method that manipulates both detail and approximation coefficients at each decomposition level, which can mitigate speckle noise while preserving impact responses in LDVom signals. The steps are as follows.

Step 1. Apply DWT to the raw signal $x(n)$ and obtain the detail coefficients $cD_i(n)$ and the approximation coefficients $cA_i(n)$ for decomposition level i (starting from 1), where n denotes the index of the time series.

$$x\left(n\right)\overset{\text{DWT}}{\underset{i=1}{\longrightarrow}}\left(cD_i\left(n\right),\ cA_i\left(n\right)\right) \tag{1}$$

Step 2. Map the detail coefficients $cD_i(n)$ to weights $w_i(n)$ through a weight function $W(\bullet)$ as follows. In general, larger detail coefficients are more affected by speckle noise locally and should be assigned lower weights.

$$w_i\left(n\right)=W\left(cD_i\left(n\right)\right) \tag{2}$$

Step 3. Perform a moving weighted average to both the detail coefficients $cD_i(n)$ and the approximation coefficients $cA_i(n)$ using the weights $w_i(n)$ as follows,

$$cD_i{}^*\left(n\right)=\frac{\sum_{j=n-N_{\mathrm{D}i}}^{n+N_{\mathrm{D}i}}cD_i(j)\cdot w_i(j)}{(2N_{\mathrm{D}i}+1)\sum_{j=n-N_{\mathrm{D}i}}^{n+N_{\mathrm{D}i}}w_i(j)}\qquad cA_i{}^*\left(n\right)=\frac{\sum_{j=n-N_{\mathrm{A}i}}^{n+N_{\mathrm{A}i}}cA_i(j)\cdot w_i(j)}{(2N_{\mathrm{A}i}+1)\sum_{j=n-N_{\mathrm{A}i}}^{n+N_{\mathrm{A}i}}w_i(j)} \tag{3}$$

where $cD^*{}_i(n)$ and $cA^*{}_i(n)$ denote the manipulated wavelet coefficients and N_{Di} and N_{Ai} represent the half window size for smoothing $cD_i(n)$ and $cA_i(n)$, respectively.

Step 4. Apply DWT to the manipulated approximation coefficient $cA^*{}_i(n)$ and obtain the wavelet coefficients at the next level, denoted again as $cD_i(n)$ and $cA_i(n)$ with i increased by 1.

$$cA^*{}_i\left(n\right)\overset{\text{DWT}}{\underset{i\leftarrow i+1}{\longrightarrow}}\left(cD_i\left(n\right),\ cA_i\left(n\right)\right) \tag{4}$$

Step 5. Repeat Steps 2∼4 until i exceeds the desired decomposition level I.

Step 6. Reconstruct the signal by applying cascade inverse DWT to the manipulated wavelet coefficients $cA^*{}_I(n)$, $cD^*{}_I(n)$, $cD^*{}_{I-1}(n)$, …, $cD^*{}_1(n)$. Denote the reconstructed signal as $x^*(n)$.

$$cA^*{}_I\left(n\right),cD^*{}_I\left(n\right),cD^*{}_{I-1}\left(n\right),...,cD^*{}_1\left(n\right)\overset{\text{Cascade inverse DWT}}{\longrightarrow}x^*\left(n\right) \tag{5}$$

This procedure is illustrated in Fig. 2, which follows a similar structure to conventional wavelet denoising but introduces key differences tailored to address the unique properties of speckle noise. These distinctions are essential for more effectively mitigating speckle noise and preserving impact responses in LDVom signals. In the proposed method,

- Both detail and approximation coefficients are manipulated, whereas, in conventional wavelet denoising, only detail coefficients are manipulated.

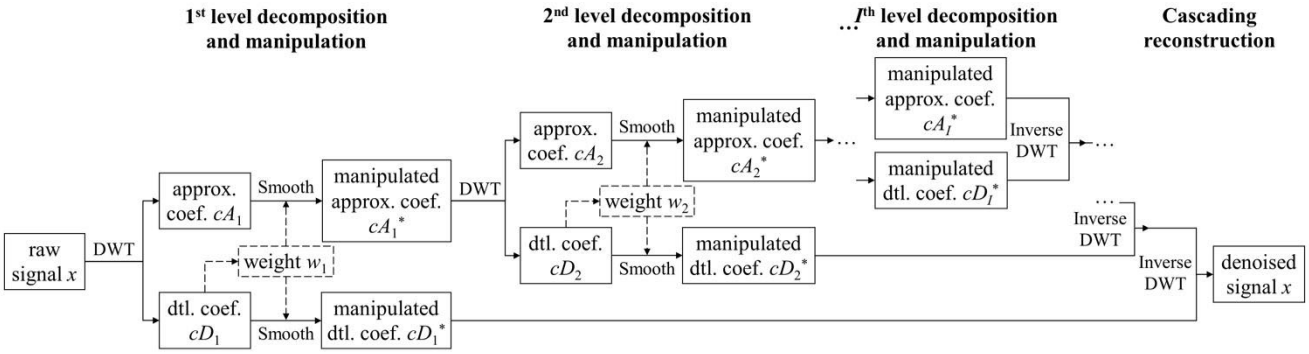

Fig. 2 Illustration of the proposed wavelet denoising method.

- The entire series of wavelet coefficients are manipulated based on the local noise intensity, whereas, in conventional wavelet denoising, only detail coefficients below certain thresholds are manipulated.
- Wavelet coefficients at locations of larger detail coefficients are assigned lower weights and are less influential to the manipulated wavelet coefficients, whereas, in conventional wavelet denoising, smaller detail coefficients are made less influential to the manipulated detail coefficients.

Several key parameters need to be selected properly in the proposed method:

- **Wavelet type**: Different wavelets are suited to capture different dynamic patterns [16]. In the proposed method, the wavelet should provide large detail coefficients exactly at locations of speckle noise. Therefore, wavelets with shapes similar to speckle noise are preferred. Considering the shape of speckle noise, as exemplified in Fig. 3 (a), the Coiflets or Symlets families [21] are recommended. Examples of these wavelets are shown in Fig. 3 (b)∼(c).
- **Weighting function**: The weighting function $W(\bullet)$ is designed to assign higher weights $w_i(n)$ to locations with less speckle noise. While detail coefficients $cD_i(n)$ are effective indicators of speckle noise, they cannot perfectly localize speckle noise due to scaling effects, phase shifts, and autocorrelation among neighboring coefficients [19][22]. Therefore, we recommend that the weight at each location should consider the detail coefficients of the location and its neighbors. An example of such a weighting function is given as follows.

$$w_i(n) = \frac{1}{\sum_{j=n-N_{\mathrm{w}_i}}^{n+N_{\mathrm{w}_i}} cD_i(j)^2} \tag{6}$$

where N_{wi} represents the number of neighbors considered on each side and it should be no smaller than the decorrelation lag of the detail coefficient as follows.

$$N_{\mathrm{w}_i} \geq \min\{k\colon\ |\mathrm{ACF}_i(k)| < \varepsilon\} \tag{7}$$

where $\mathrm{ACF}_i(k)$ represents the autocorrelation of $cD_i(n)$ at lag k and ε is a small number.

- **Window sizes**: To effectively smooth the wavelet coefficients without overly compromising local signal behaviors, such as impact responses, we recommend tuning the window sizes based on the following relationship. This relationship suggests that N_{Di} and N_{Ai} should be larger than N_{wi} to incorporate more neighboring points in the moving average process. N_{Di} is recommended to be larger than N_{Ai} as the detail coefficients primarily represent speckle noise and require more aggressive smoothing, whereas the approximation coefficients may have broadband responses and should not be smoothed excessively.

$$N_{\mathrm{w}_i} < N_{\mathrm{A}i} < N_{\mathrm{D}i} \tag{8}$$

- **Decomposition level**: The decomposition level I determines the maximum level at which the wavelet coefficients can be manipulated. We recommend increasing it incrementally from level 1 until the denoising result begins to deteriorate, e.g., the impact response gets overly smoothed.

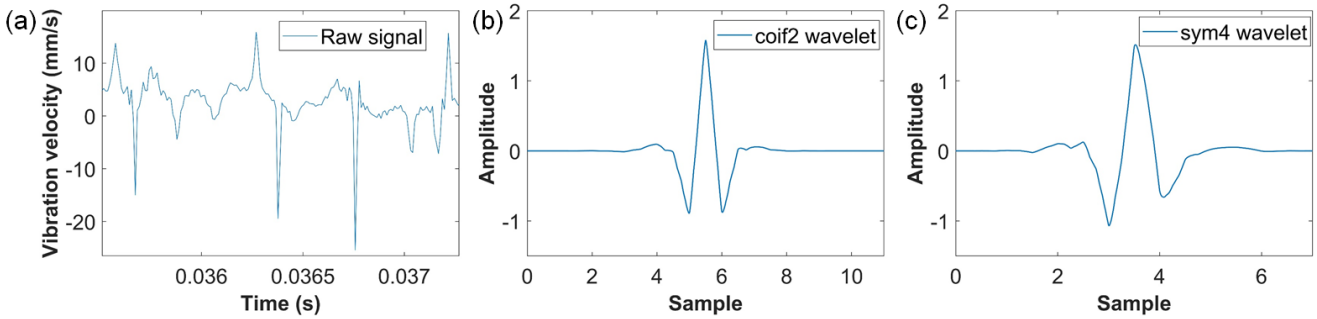

Fig. 3 Selecting wavelet to capture speckle noise into detail coefficients. (a) Examples of speckle noise in a raw LDVom signal; (b) a 2^{nd}-order Coiflet wavelet; (c) a 4^{th}-order Symlet wavelet.

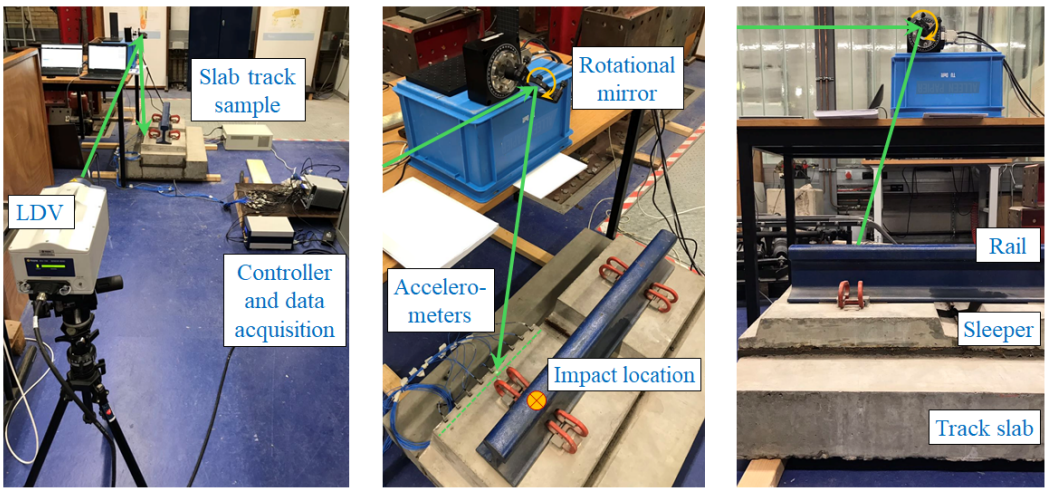

Fig. 4 Experimental setup of Case 1.

Validation Case 1

The developed denoising method is validated through two experimental case studies. In Case 1, a full-scale slab track sample subjected to manual impact excitations is measured by an LDVom. The experimental setup is shown in Fig. 4. An LDV is placed at a distance from the slab track sample, and its laser is directed onto one of the concrete sleepers by a rotational mirror. By controlling the rotation of the mirror, the laser scans the sleeper along its longitudinal direction, resembling LDV scanning from a moving train. The vibration of the sleeper is generated by manually hitting the rail head, exciting the dynamics of the slab track over a wide range of frequencies. At the same time, an array of accelerometers placed along the scanning path measures the sleeper vibration for comparison. Both the LDV and accelerometer signals are acquired through a data acquisition system at a sampling rate of 102.4 kHz.

The measurement and denoising results at two different scanning speeds are shown in Fig. 5. The impact response begins with a sudden drop and then gradually decays with both high-frequency and low-frequency oscillations. Speckle noise with random occurrence and varying amplitude can be observed, which is more severe at the higher scanning speed. The proposed denoising method is applied to the raw signals using the 2^{nd}-order Coiflet wavelet and the parameters N_{wi}=2, N_{Ai}=3, N_{Di}=5, and I=1. A low-pass (LP) filter is applied at the final stage to smooth the signals. It can be seen from the upper plots that the speckle noise is effectively eliminated. The accelerometer closest to the laser spot during the impact is selected, and its signal is converted to velocity through integration. It can be seen that the denoised results closely match the accelerometer response.

Then, the proposed method is compared with two other denoising methods in the lower plots of Fig. 5. The first comparison is with the detection-based method adapted from [14], which detects speckle noise and then replaces it with predictions from time series models. In both examples, the impact response is distorted since some points are mistakenly detected as speckle noise and replaced. Meanwhile, the prediction error during the impact response is large due to the strong nonstation-

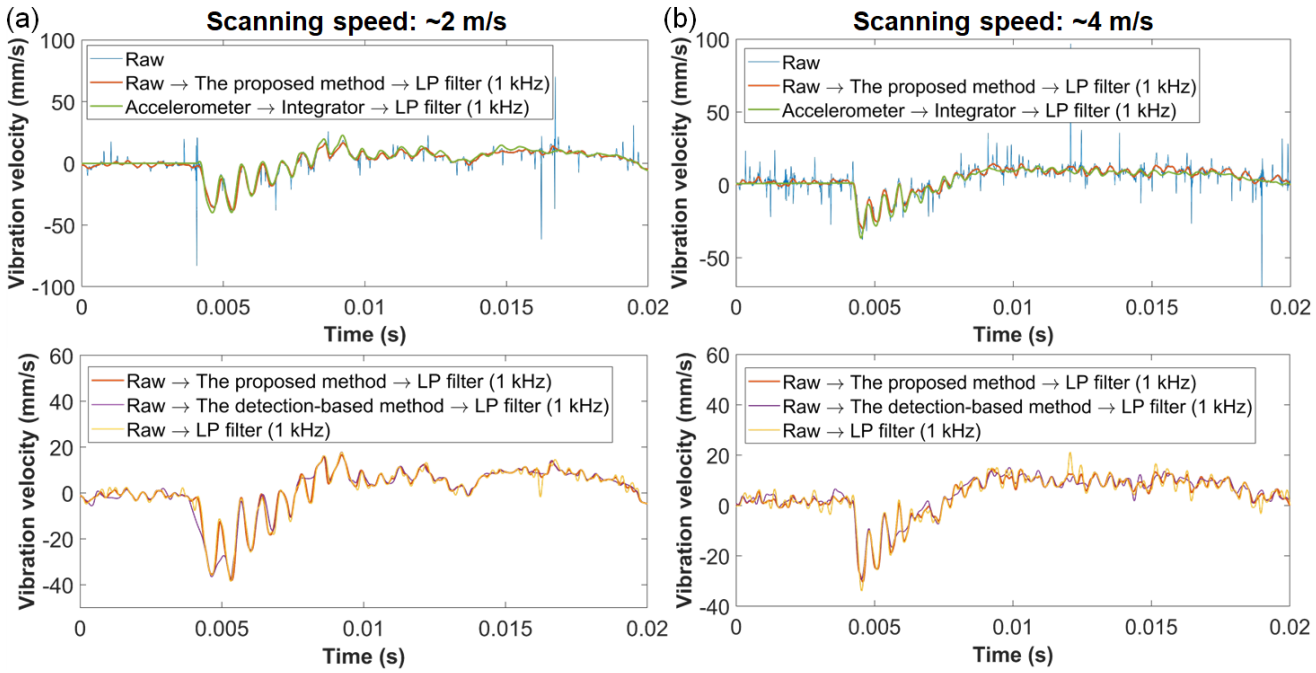

Fig. 5 Measured signals and denoising results in Case 1 (Upper plots: comparison with accelerometer signals; Lower plots: comparison with the other denoising methods). (a) At the scanning speed of around 2 m/s; (b) At the scanning speed of around 4 m/s.

arity. For instance, significant speckle noise occurs at the instant of the impact in Fig. 5 (a), but the time series model cannot anticipate the sudden impact, thus producing large prediction errors. The second comparison is with the direct use of the LP filter. While the filter covers the frequency range of the impact response, it also retains some speckle noise components. This smooths large-amplitude speckle noise into vibration-like patterns, inducing additional errors in the denoised signals. In contrast to the two methods, the proposed method reduces speckle noise without distorting the impact response or inducing additional disturbances, demonstrating its effectiveness at different scanning speeds.

Validation Case 2

The 2$^{\text{nd}}$ case study extends the validation by testing the denoising method using impact responses measured under operational conditions. It is conducted on the TU Delft V-Track test rig [23], as shown in Fig. 6. The test rig replicates wheel-rail interaction with scaled vehicle and track structures. An LDV is mounted on the test rig, and its laser beam is reflected by a mirror and pointed onto the rail. As the test rig operates, the wheel runs along the rail, and the LDV measures the rail vibration caused by the wheel-rail contact. Impacts occur at local irregularities, such as the rail joint in Fig. 6. The LDVom signal near this rail joint is used to test the developed method. Accelerometers are mounted on the rail near the joint for comparisons. Moreover, an accelerometer is mounted on the mirror to compensate for the influence of the mirror vibration on the LDVom signal. Both the LDV and accelerometer signals are acquired at a sampling rate of 102.4 kHz.

The measurement and denoising results at two different running speeds are shown in Fig. 7, in which the influence of the mirror vibration has been removed. The dynamic response over the joint first begins with a gradual increase, followed by the sudden and decaying impact response. As the running speed increases, the impact response becomes larger, and the speckle noise becomes more severe. The proposed denoising method, using the same wavelet type and parameters as Case 1, is applied to the raw signals. It can be seen that the speckle noise is effectively removed and the denoised signals are close to the vibration measured by the accelerometer on the rail.

The results are further compared with the other two denoising methods in Fig. 7. The detection-based method again distorts the impact responses due to inaccurate detection and prediction. The LP filter retains some components of the speckle noise. The results demonstrate the effectiveness of the proposed method in removing the speckle noise and cap-

turing the impact response under operational conditions. It is noteworthy that the same wavelet type and parameters are used for the two validation cases at different speeds, highlighting the generalizability and robustness of the proposed methods.

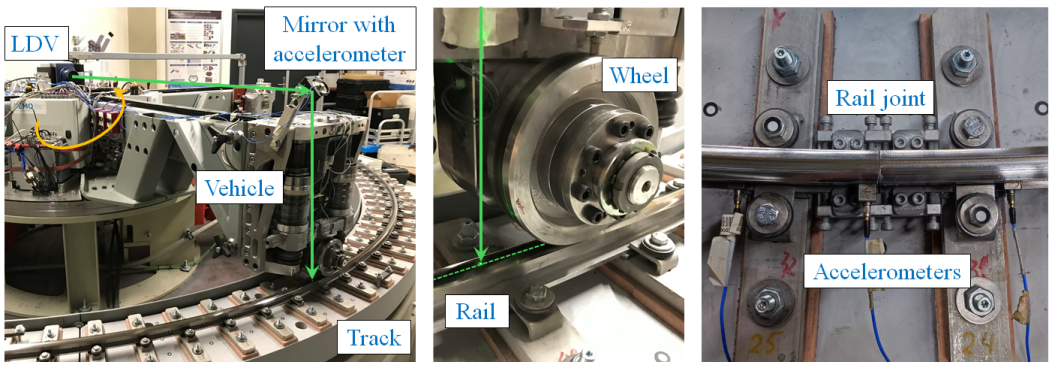

Fig. 6 Experimental setup of Case 2.

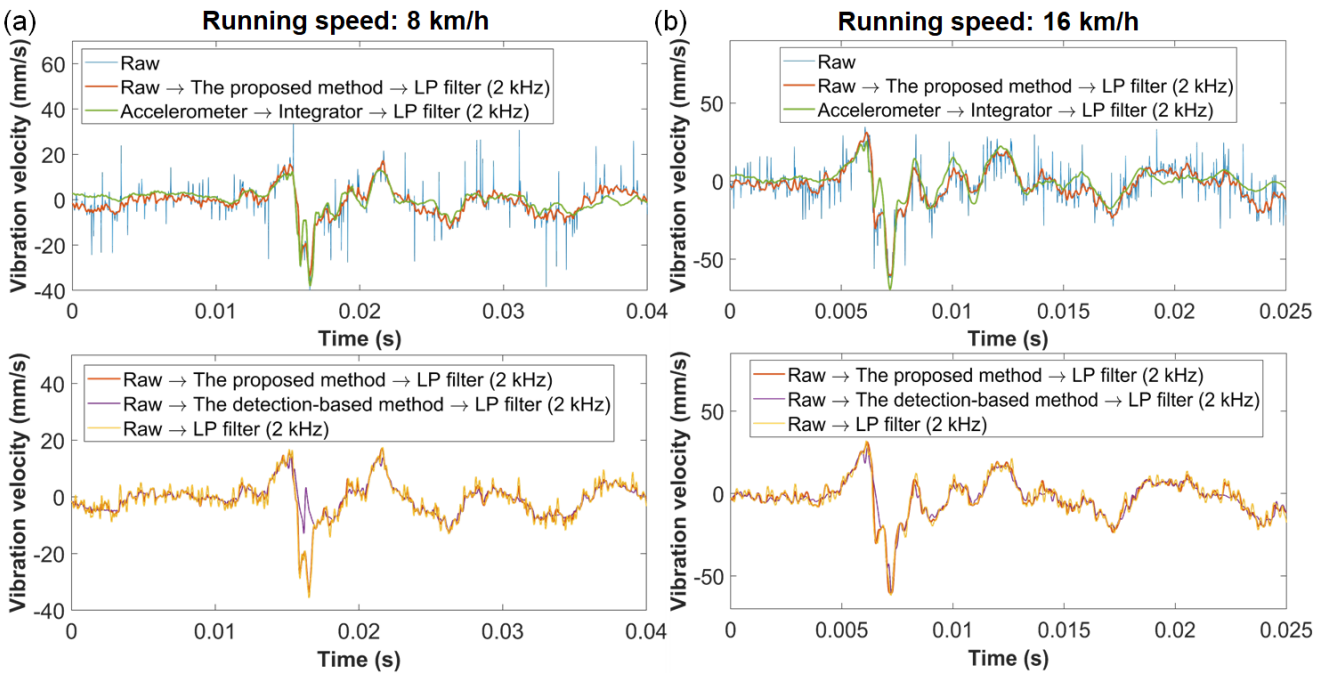

Fig. 7 Measured signals and denoising results in Case 2 (Upper plots: comparison with accelerometer signals; Lower plots: comparison with the other denoising methods). (a) At the running speed of 8 km/h; (b) At the running speed of 16 km/h.

Conclusion

This paper presents a novel wavelet denoising method for mitigating speckle noise while preserving impact responses in LDVom signals. The method adapts conventional wavelet denoising by manipulating both approximation and detail coefficients at each decomposition level to address the unique characteristics of speckle noise. Experimental validation is conducted under varying conditions and scanning speeds. The conclusions are summarized as follows.

- Conventional wavelet denoising is unsuitable since it removes only small detail coefficients, leaving speckle noise mostly unaddressed. DWT cannot effectively separate speckle noise from impact responses.
- Using wavelets with shapes similar to speckle noise, such as the Coiflets or Symlets families, can effectively indicate speckle noise in the time series. Manipulating both approximation and detail coefficients based on the local intensity of speckle noise in the time series can effectively mitigate speckle noise.
- The proposed method can effectively capture the impact responses in the LDVom signals with reduced speckle noise. The results match closely with the accelerometer measurements, and the method outperforms the two denoising methods under comparison.

The proposed method enables impact responses to be accurately captured by LDVom, which can potentially be used in various fields, including defect detection and modal identification. Future research will focus on designing wavelet functions that better resemble speckle noise characteristics and incorporating a smoothing step within the denoising framework.

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