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Normal Paper

Automating Vibration Analysis: Optimized Multi-Delay Filters for Improved Signal Separation

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Abstract

A common challenge in vibration analysis of rotating machinery is the isolation of signal contributions from individual mechanical components. Many vibration characterization and fault detection methods benefit from separating deterministic from stochastic signal content. Various techniques aim to achieve this by distinguishing periodic signals from broadband signals. This paper focuses on the Discrete/Random Separation method, which estimates a frequency domain transfer function to separate predictable periodic content from random signal content. While this method has demonstrated its performance in terms of separation accuracy and computational efficiency, it still faces drawbacks such as the variance of the estimated filter and its dependency on the choice of time delay. This paper further investigates the potential improvements by extending the filter definition from a single-delay to a multi-delay filter estimation. This extension mitigates the impact of an incorrect filter delay choice and enhances separation accuracy due to the reduced variance of the estimated filter. Additionally, this work explores optimizing the input parameters of the method, minimizing the trial-and-error process typically required to determine appropriate delays and window sizes. This optimization enables a more user-friendly, almost blind usage of the method. The study first showcases the statistical properties of the improved multi-delay discrete-random separation filter and the automatic parameter optimisation. These findings are then validated using a complex simulated dataset and an experimental vibration dataset from a large industrial pump. The results illustrate the reliability and accuracy of the novel multi-delay Discrete/Random Separation method, while highlighting its ability to be used in a fully automated manner.

Keywords: Automated Parameter Optimization, Multi-Delay Filter Estimation, Vibration Signal Separation, Condition monitoring.

Introduction

Vibration signal processing frequently necessitates the separation of signal components to enhance the analysis of individual elements. A common approach involves partitioning signals into deterministic and stochastic components, as measured vibrations typically result from multiple sources falling into these categories. Ideally, this separation should be automated, minimizing the need for input parameters or prior knowledge. This challenge extends beyond vibration analysis to other periodic signals, such as acoustical and electrical signals.

A primary motivation for incorporating this separation into machinery vibration monitoring is the improved detection of mechanical faults. For instance, bearing faults are frequently identified through the analysis of the signal's envelope spectrum [1,2,3,4,5,6]. However, high-energy deterministic components can obscure fault indicators, necessitating effective separation techniques. Bearing fault signals are considered stochastic due to random jitter in the fault frequency's fundamental period [1], resulting in smeared frequency components. In contrast,

deterministic signals appear as distinct spectral peaks. Separating these components not only aids fault detection but also enhances modal analysis by removing interfering harmonics that can distort resonance frequency and damping estimates [7,8].
Deterministic content analysis is equally valuable, particularly for identifying gear faults, which manifest as changes at harmonics of the gear's rotational speed [9]. Isolating these deterministic signals from background noise enhances the efficiency of subsequent analysis techniques that rely on discrete spectral lines [10]. Gear signals are regarded as deterministic since gears are mechanically phase-locked to the operating rotational speed, producing equidistant harmonic peaks in the frequency domain.

Current methods for stochastic-deterministic separation leverage the statistical differences between these signal classes. Techniques such as linear prediction filtering (LP), comb filtering, adaptive line enhancers, time synchronous averaging (TSA), cepstrum editing, phase editing, self-adaptive noise cancellation (SANC), and discrete/random separation (DRS) have been developed [11,12,13]. Among these, the original DRS method [12], introduced in 2004, estimates a frequency domain filter based on the correlation length differences between stochastic and deterministic components. While effective, it relies on a single time delay, making it sensitive to parameter choices and resulting in high filter variance, which can hinder the discrimination of closely spaced harmonic peaks.

To address these limitations, we propose an enhanced multi-delay DRS method. By utilizing multiple time delays, the new approach averages filters across various delays, significantly reducing variance and simplifying filter estimation. This extension not only improves performance but also offers greater flexibility for real-world applications. Compared to other state-of-the-art methods, the multi-delay DRS does not require model order inputs, avoids the cumbersome parameter settings of TSA, and maintains computational efficiency without the convergence issues seen in SANC. Although it requires an approximate estimate of the instantaneous angular speed (IAS), this can be reliably obtained from vibration signals using established techniques [14]. Furthermore, this study focuses on optimizing the DRS-MD method's input parameters, significantly reducing the trial-and-error typically involved in selecting appropriate delays and window sizes. This optimization facilitates a more user-friendly and nearly automated application of the technique. Initially, we present the statistical properties of the DRS-MD filter and its automatic parameter optimization before validating these findings on both a complex simulated dataset and experimental vibration data from a large industrial pump.

Methodology

In the original DRS paper, the technique employs a single delay to estimate the filter. This approach is based on the assumption that deterministic components are predictable, allowing for the existence of a filter that aligns a delayed version of one signal block with another, specifically targeting the discrete content. Mathematically, this can be expressed by minimizing the mean squared error as follows:

$$MSE = \langle \left|\left|X(f) - H(f)X_{\Delta}(f)\right|\right|^2 \rangle \tag{1}$$

with X(f) the Fourier transform of a vibration signal x(t), $X_{\Delta}(f)$ the Fourier transform of the delayed signal $x_{\Delta}(t)$, the brackets $\langle .. \rangle$ are used to represent taking the average, and H(f) is the frequency domain filter. The filter that minimizes the MSE is equivalent to the ratio of the averaged cross-power spectra of the signal and its delayed version and the averaged autopower spectra and given in Eq.2:

$$\widehat{\mathrm{H}}_{\mathrm{DRS}} = \frac{\left\langle X^i(f) X_{\Delta}^i(f)^* \right\rangle}{\langle |X_{\Delta}^i(f)^2| \rangle} \tag{2}$$

Moreover, the variance of the filter can become significantly high depending on method parameters such as window length and FFT size. To address this, we propose estimating the DRS filter using multiple delays, typically employing smaller windows instead of a single delay with a long window. This approach allows the transfer functions corresponding to different delays to be averaged. The primary advantage of this method is the reduction in filter variance and the narrowing of the main lobe in the frequency domain filter. Additionally, using a range of delays provides the end-user with greater flexibility in parameter selection, making the results less reliant on the optimal choice of a single parameter. This enhancement not only improves the filter's performance but also simplifies its application in diverse real-world scenarios.

Extending Eq.2 for the multi-delay case with I delays, gives:

$$H_{multi}(f) = \frac{1}{\sum_{i=1}^{I} c_i} \sum_{i=1}^{I} c_i H_{\Delta_i}(f) \tag{3}$$

with c_i the weight for filter $H_{\Delta_i}(f)$. These weights can aid in minimizing the filter's bias and roll-off; however, in this study, they are assumed to be uniform (all ones) and are not explored further. The primary factor contributing to the variance reduction, compared to the single-delay filter approach, is the phase alignment. Specifically, the phases facilitate constructive averaging of the transfer function at harmonic frequencies, enhancing the filter's effectiveness.

Simulated application

To assess the performance of the proposed methodology in a controlled and easily reproducible manner, this section examines a simulated data case. A complex vibration signal is simulated that consists out of a hundred harmonics and additive white Gaussian noise that pass through four lightly damped resonances. The signal has a length of L=10^5 samples. The used DRS window length is 3×10^3 with an FFT size of 20 times the window length. For the single-delay DRS, a delay of 1 period of the lowest frequency harmonic is used while for the multi-delay DRS ten delays between 1 to 200 periods of the same harmonic are randomly picked. Figure 1a shows the amplitude spectrum of the generated signal mixture used as input for the DRS and DRS-MD methods. The residual noise spectra after filtering are displayed in Fig. 1b, highlighting that both DRS and DRS-MD are quite capable in removing the majority of deterministic content while preserving the shape of the spectral noise floor. The corresponding filter gains are shown in Fig.2 for both the single- and multi-delay DRS. Due to the presence of many harmonics, it is somewhat difficult to see from Fig. 2a that the bandwidths of the filter peaks for the proposed method are again significantly smaller than for the standard DRS. Therefore, Fig. 2b provides a smaller frequency range of the same frequency gains. As can be seen, the proposed DRS-MD method manages to estimate a much more accurate separation filter.

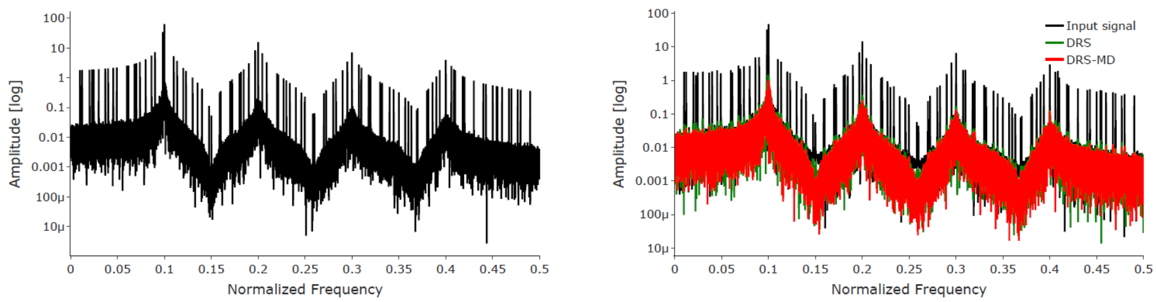

Figure 1: Amplitude spectra of the complex signal mixture before filtering (left) and after filtering (right).

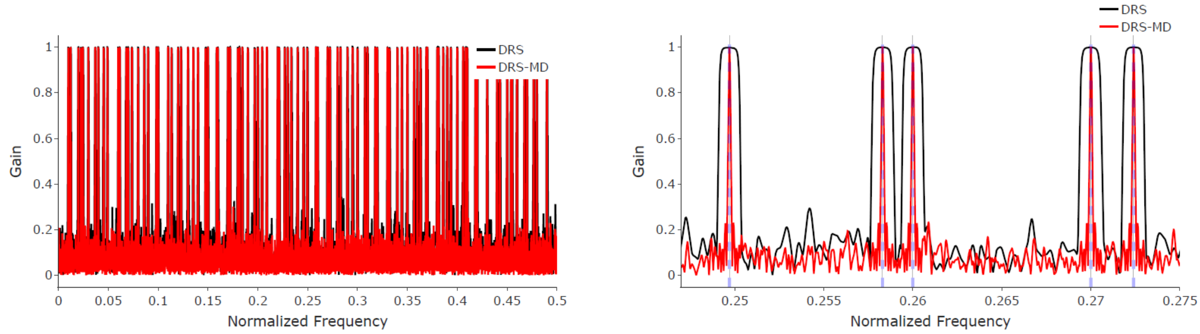

Figure 2: Comparison of the frequency gain of DRS-MD algorithm (red)and DRS (black) for a complex signal mixture for the full frequency range (left) and a zoomed subset (right).

Although the proposed multi-delay extension of the discrete-random separation (DRS-MD) filter streamlines the user's workflow, it still requires the selection of appropriate window lengths and delay ranges. Consequently, when analyzing new data, it remains important to quickly identify suitable input parameter settings. This section therefore examines the potential for automating the selection of window sizes and delay ranges for DRS-MD. Preliminary empirical results indicate that window size is typically the most critical parameter to adjust for achieving accurate filter estimates. Consequently, the optimization of window size is prioritized.

To determine an appropriate window size, a quality metric is essential. Initially, a sparsity metric on the estimated filter was considered, expecting many values near zero and some near one. However, this metric worked well for simulated data with high SNR harmonics but resulted in overly sparse filters for noisy experimental data. Consequently, a more effective criterion focuses on the residual signal after filtering, which should ideally be free of harmonics. The cepstrum [7] is used to assess harmonic presence by segregating modal content into low quefrencies and rahmonic peaks into higher quefrencies, where only low-amplitude noise and harmonic peaks remain, making it ideal for sparsity minimization. To evaluate the performance of an estimated filter, the Hoyer Index (HI), a normalized sparsity metric, is calculated on the real cepstrum of the residual signal after filtering. Hence, to find this optimal filter, the Hoyer Index of the residual cepstrum needs to be minimized.

The multi-delay DRS is applied across window sizes ranging from 3e4 to 3e5 samples in increments of 100 samples. For each window size and corresponding filter, the real cepstrum of the residual signal is calculated, and its Hoyer index is recorded. To validate the use of cepstral sparsity as an optimization metric, Fig. 3a illustrates that lower Hoyer index values correspond to minimized mean squared error (MSE) for the periodic signal content. This correlation confirms that the Hoyer index of the residual signal's real cepstrum is effective for automated window size selection, even for a complex case. After window size, the delay range is typically the second most influential input parameter affecting the results of DRS-MD. As shown in Fig. 3b, using ten delays is generally sufficient for accurate filter estimation across most window sizes.

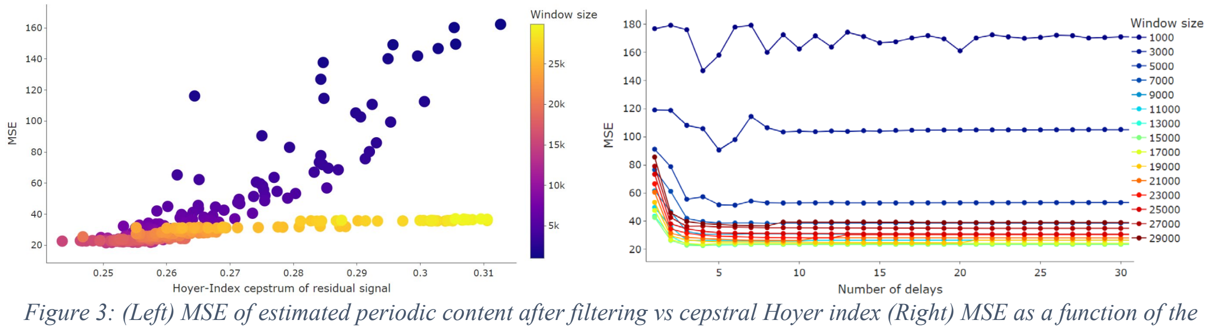

Figure 3: (Left) MSE of estimated periodic content after filtering vs cepstral Hoyer index (Right) MSE as a function of the number of delays used for the filter estimation. For most window sizes the error stabilizes when using 10 or more delays.

Experimental application

The experimental case study investigates the performance of the proposed DRS-MD filtering on vibration data of a gearbox installed in a large industrial multi-megawatt pump. The gearbox consists of a planetary stage linked to a differential gear set. A vibration measurement of 1 minute long, sampled at 31.25kHz, is analysed. Given the complexity of the gearbox and the nature of the physical pumping process, the number of harmonics observed in the measured vibration spectra is again very high, in excess of 4000 easily distinguishable harmonics can be counted in the full bandwidth spectrum.

The window size optimisation is also repeated here. The used window size search range again varies from 0.5 seconds to 6 seconds, along with ten delays between 0.5 seconds to 4 seconds. Figure 4a indicates that the optimal result for filtering is attained by a window size of 66500 samples or 2.1 seconds. The amplitude spectra of the raw measured signal and the DRS filtered signals after angular resampling are displayed in Fig. 4b. The reference order of 1 is the rotation speed of the planet carrier of the planetary gearbox. From this full-bandwidth spectrum, it can be seen that both DRS methods are very effective at removing the majority of visible discrete peaks and do not affect the rest of the spectrum much. Lastly, the reduction in bandwidth for the DRS-MD filter as compared to the single-delay DRS is again examined in Figs. 5a & 5b for the frequency regions that correspond with the amplitude spectra shown in Fig. 4b. The DRS-MD filter again delivers more narrow filter peaks whilst maintaining the same noise floor and peak levels.

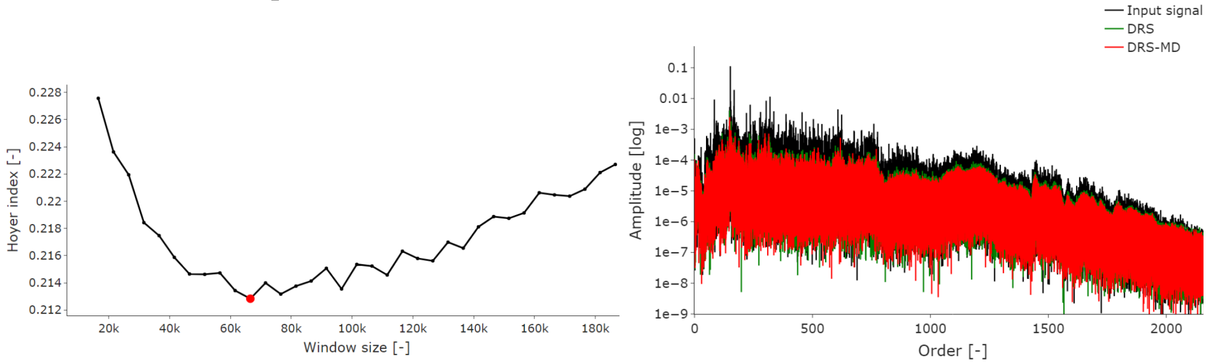

Figure 4: (Left) Trend of cepstral Hoyer index after filtering for different window sizes. (Right) Amplitude spectra of the experimental signal (black) and the filtered stochastic content after DRS (green) and DRS-MD (red).

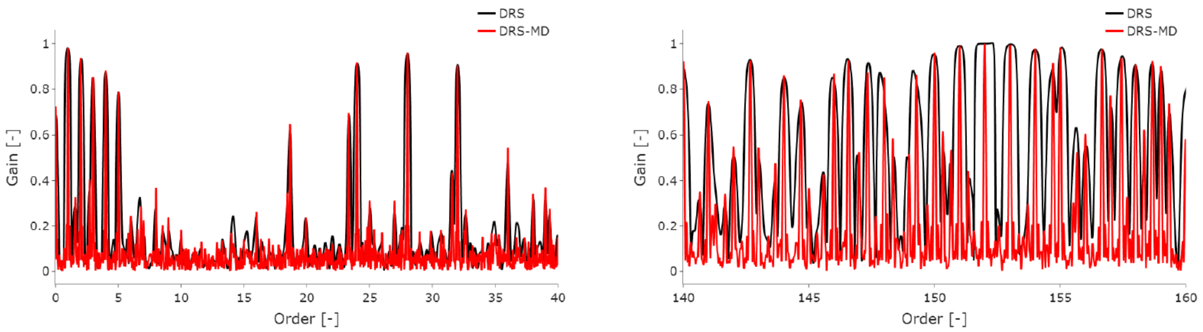

Figure 5: Zoom of the filter gains of DRS and DRS-MD for a low-frequency range (left) and a high-frequency range (right).

Conclusions

Based on the simulated and experimental case studies, the proposed multi-delay Discrete-Random Separation (DRS-MD) method significantly outperforms the single-delay DRS in terms of filter variance, separation accuracy, and ease of use. Compared to other state-of-the-art techniques like cepstral liftering and self-adaptive noise cancellation, DRS-MD provides superior estimates of both periodic and random content. While DRS-MD offers end-users greater flexibility by allowing the use of multiple delays instead of a single one, it still requires users to select an appropriate range of delays, which is typically data-dependent. This necessitates some initial setup time to ensure effective filtering when processing new data sources. However, the multi-delay approach achieves reliable results more quickly than the single-delay method and demonstrates increased robustness to data variability. This paper presents an empirical method for automatically determining a reliable filter estimate by minimizing the sparsity of the cepstrum of the residual stochastic signal. Future work will aim to enhance reliability further by integrating an optimization procedure for selecting the delays used.

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