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Normal Paper

Enhanced multi-order probabilistic approach for rotation speed estimation using the short-time Iterative Adaptive Approach

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Abstract

The multi-order probabilistic approach is a time-frequency-based signal processing method to estimate the instantaneous angular speed of a rotating shaft using vibrations. It exploits the fact that most rotating machines consist of multiple shafts and gears that produce strong, deterministic vibrations. These periodic vibrations show up as families of harmonics in spectral analysis. The multi-order probabilistic approach employs the short-time Fourier transform or STFT to estimate the non-stationary instantaneous angular speed since it is a robust, non-parametric time-frequency decomposition that does not suffer from cross-terms, performs well at low signal-to-noise ratios, and has a low computational cost. Nowadays however, there are new high-resolution non-parametric spectral estimators that have positioned themselves as potential alternatives to the STFT. One promising alternative is the short-time Iterative Adaptive Approach or ST-IAA which offers a higher resolution than the STFT in exchange for an increased computational cost. This paper investigates the potential of the ST-IAA to enhance the accuracy of the multi-order probabilistic approach since it allows to employ shorter time windows while reducing sidelobes and leakage. The performance of the method is evaluated on experimental vibration data measured on the gearbox of a civil aircraft engine. To properly assess the accuracy of the ST-IAA-based multi-order probabilistic approach, it is compared to several other state-of-the-art vibration-based speed estimation techniques. The results show that the ST-IAA-based multi-order probabilistic approach can reliably outperform the conventional STFT-based version.

Keywords: vibration signal processing, time-frequency analysis, instantaneous rotation speed estimation, condition monitoring.

Introduction

Spectral analysis of one-dimensional, non-stationary, time-domain signals plays a vital role in many signal processing methodologies. In the field of machine monitoring, spectral analysis of such non-stationary signals is of particular interest to the research community due to the presence of this type of signals in many industrial applications. A concrete example is the inherent non-stationary nature of most rotating machines. In order to analyse measurement data originating from a machine operating in non-stationary conditions, a commonly employed approach is to visualize a time-frequency representation (TFR) of the data. This data can involve measurements of the machine vibrations, currents, or acoustics. Visualizing the TFR of these signals can be valuable for various reasons and has therefore been used for multiple different purposes. In general, there has been ample research in the last few decades that tries to improve existing TFR methods, resulting in many new techniques for TF decompositions [1,2,3,4,5,6].

Currently, the STFT is the most used TFR method in non-stationary vibration analysis since it is an easy-to-interpret, non-parametric method with low computational complexity. Importantly, the STFT is also reliable for the analysis of complex vibrations that contain an unknown number of non-stationary signal components with varying or low signal-to-noise ratios (SNR), which is a property that is not always shared by some other, typically parametric, developments that need a prior estimate of the number of signal components. Automated vibration processing methodologies for machine monitoring benefit and typically require a method that does not require any data-dependent hyperparameter setting to ensure robustness in strongly varying operating conditions. Practically speaking, when large amounts of highly variable vibration data need to be processed, it is simply not feasible to optimize these hyperparameters for each dataset manually and the optimization itself can be very complex to automate reliably.

This paper investigates the potential of an adaptive spectral estimation alternative for post-processing of non-stationary vibrations as opposed to the conventional STFT. The sliding-window or short-time iterative adaptive approach (ST-IAA) is a high-resolution data-dependent filterbank-based approach that offers a reduction in leakage effects in exchange for a higher computational complexity. This work analyses the performance of the ST-IAA on complex vibration signals with a focus on how it can improve the estimation of the instantaneous angular speed when compared to the STFT.

The multi-order probabilistic approach is a highly effective, reliable vibration-based rotating speed estimation technique. Currently, it employs the STFT for constructing a probability-based 2D map of the instantaneous rotating speed. Replacing the STFT by an improved alternative such as the ST-IAA thus sounds particularly appealing, however, care needs to be taken with regard to the conservation of reliability and ease of use that the STFT presently offers. While the STFT has been tested extensively on data coming from many different vibration sources, the ST-IAA has not. Therefore, this work expands the so far limited application scope of the ST-IAA by investigating a more challenging experimental data source, i.e. an aircraft engine gearbox.

Methodology

The short-time Fourier transform is the current staple analysis tool for non-stationary vibration signal processing thanks to it being a robust, non-parametric, and computationally efficient technique to analyze non-stationary signals through a time-frequency representation. However, despite the beneficial properties, the short-time Fourier transform also suffers from high variance, high sidelobes, and a low resolution. This section introduces an alternative to the STFT for vibration processing and in particular for instantaneous angular speed (IAS) estimation.

The Iterative Adaptive Approach (IAA) is a spectral estimation technique based on an iterative weighted least-squares method that is non-parametric. It has been shown in the past that the IAA can reduce sidelobe levels and yield a higher resolution than the standard periodogram. Additionally, it also returns a dense (i.e. not sparse) estimate of the signal power spectrum which can be beneficial when dealing with complex vibrations, since enforcing sparsity typically involves parameter tuning. IAA assumes that the vibration data adheres to the following signal model:

$$\boldsymbol{y_N} = \boldsymbol{F_{N,K\alpha_K}} + \boldsymbol{e_N} \tag{1}$$

with $\boldsymbol{y_N}$ being the vibration signal of length *N*, $\boldsymbol{F_{N,K}} \triangleq [\boldsymbol{f_N}(\omega_0), \boldsymbol{f_N}(\omega_1), \dots, \boldsymbol{f_N}(\omega_{K-1})]$ the Fourier matrix of size *NxK*, $\boldsymbol{\alpha_K} \triangleq [\alpha(\omega_0), \alpha(\omega_1), \dots, \alpha(\omega_{K-1})]^T$ the complex-valued spectral amplitudes at the frequencies ω_k, and $\boldsymbol{e_N}$ an additive noise. IAA tries to estimate $\boldsymbol{\alpha_K}$ from Eqn.1 by minimizing the following weighted least-squares cost function:

$$\left|\left|\boldsymbol{y_N} - \boldsymbol{f_N}(\omega_k)\alpha_k\right|\right|^2_{\boldsymbol{Q_N^{-1}}(\omega_k)}, k = 0,1,\dots,K-1 \tag{2}$$

where $\left|\left|\boldsymbol{z}\right|\right|^2_{\boldsymbol{Q_N^{-1}}(\omega_k)} \triangleq \boldsymbol{z^H}\boldsymbol{Q_N^{-1}}(\omega_k)\boldsymbol{z}$ and $\boldsymbol{Q_N}(\omega_k) = \boldsymbol{R_N} - p_k\boldsymbol{f_N}(\omega_k)\boldsymbol{f_N^H}(\omega_k)$. $\boldsymbol{Q_N}(\omega_k)$ is the noise and IAA interference (signals at frequency grid points bar ω_k) covariance matrix for the k^{th} grid point. The signal power is denoted by $p_k = |\alpha_k|^2$ and the IAA covariance matrix is given by:

$$\boldsymbol{R_N} = \boldsymbol{F_{N,K}}\boldsymbol{P_K}\boldsymbol{F^H_{N,K}} \tag{3}$$

with $\boldsymbol{P_K}$ a diagonal matrix with p_k on its main diagonal. Minimisation of Eqn.2 for α_k (with p_k kept constant) results in:

$$\alpha_k^{IAA} = \frac{\boldsymbol{f_N^H}(\omega_k)\boldsymbol{Q_N^{-1}}(\omega_k)\boldsymbol{y_N}}{\boldsymbol{f_N^H}(\omega_k)\boldsymbol{Q_N^{-1}}(\omega_k)\boldsymbol{f_N}(\omega_k)},\ k = 0,1,\dots,K-1. \tag{4}$$

This can be simplified using Eqn.3 and the matrix inversion lemma [12] to:

$$\alpha_k^{IAA} = \frac{\boldsymbol{f_N^H}(\omega_k)\boldsymbol{R_N^{-1}}(\omega_k)\boldsymbol{y_N}}{\boldsymbol{f_N^H}(\omega_k)\boldsymbol{R_N^{-1}}(\omega_k)\boldsymbol{f_N}(\omega_k)},\ k = 0,1,\dots,K-1. \tag{5}$$

Eqn. 5 reduces the computational cost drastically since it does not necessitate the computation of $\boldsymbol{Q_N^{-1}}(\omega_k)$ for each frequency bin *k*.

Since the signal power P_K is required in Eqn.5, the IAA estimate needs to be computed iteratively. In this paper, the periodogram is used to initialize the IAA estimate. To speed up computations significantly, the superfast implementation of the IAA using the suitable Gohberg–Semencul representations and the preconditioned conjugate gradient method is applied using an incomplete factorization of the Toeplitz matrix [13]. Finally, to compute the short-time IAA (ST-IAA) time-frequency representation, a sliding window approach is used similar to the STFT.

To illustrate the benefit in using the ST-IAA instead of the STFT, this paper investigates the former's impact on instantaneous speed estimation using the multi-order probabilistic approach (MOPA). A concise summary of MOPA is presented here but interested readers are referred to [7,8,9,10,11] for more in-depth information.

The main idea behind the multi-order probabilistic approach (MOPA) as originally proposed by Leclère et al. [7] is based on regarding the instantaneous spectrum of the vibration signal as a probability density function of the IAS. Consequently, if the spectrum has a high amplitude at frequency *f*, there is a high probability that the shaft frequency of interest is equal to f/H_i with H_i being the i$^{\text{th}}$ excitation or harmonic order.

To improve the IAS estimation and utilize more of the information potential of the spectrum, one has to include more than just one pdf based on one gear ratio or meshing order. These different pdfs can then be combined in one pdf by multiplication. Since pdfs are independently generated for each time step, they do not guarantee any continuity of the IAS, which is typical for any mechanical system. Due to the inertia of the rotating shafts, sudden strong acceleration or deceleration jumps are improbable. Therefore, an a priori of continuity is introduced for the IAS. The concept relies on generating for each time step a pdf that is based on the pdfs of several time steps before and after the central pdf. Appropriate weighting of these pdfs is done by convolving the pdf with a centred Gaussian and the time relationship is introduced by letting the variance depend on the time between the considered pdf and the central pdf. The parameters of the centred Gaussian can be decided based on the max expected acceleration of the IAS. The final IAS estimate can then be extracted from the two-dimensional pdf map as the expected value over time in the predefined IAS range. MOPA has proven to be a reliable and accurate IAS estimation tool in the past thanks to its ability to take many harmonic orders into account simultaneously. The next section then compares the performance of the STFT-based MOPA with the ST-IAA-based MOPA.

Experimental application

The used data set comes from the Safran contest at the Surveillance 8 conference, held in Roanne, France [14]. The dataset contains vibration and tachometer measurements from a ground test campaign on a civil aircraft engine with two damaged bearings. The gearbox is displayed in Fig. 1a and consists of two main shafts and an accessory gearbox with equipment such as filters, alternators, pumps, and starter. A radial drive shaft (RDS) and a horizontal drive shaft (HDS) link the high-pressure shaft (HP) to the accessory gearbox. A spectrogram of the analysed signal of accelerometer 2, generated using a Hanning window with a length of 2^{11} samples with an overlap of 95%, is shown in Fig.1b.

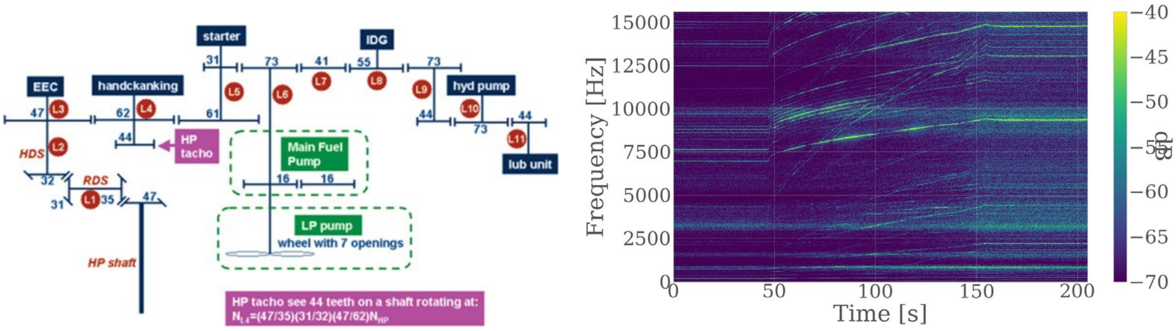

Figure 1: (Left) Diagram of the kinematics of the gearbox, (right) Spectrogram of the analysed Surveillance 8 aircraft engine vibration data, measured by accelerometer

As shown in Fig.1b, the runup that starts at 47 secs is quite significant with respect to both the total frequency change and the acceleration. Both the STFT- and ST-IAA-based MOPA methods are applied on this data set with identical input parameters. In this case, the chosen window length is 0.1 secs with an overlap of 80% for calculating the STFT and ST-IAA. MOPA itself uses a set of 30 harmonics based on the kinematic orders of the gearbox with a fundamental frequency range going from 175 Hz to 250 Hz. To enhance the performance assessment and provide a benchmark reference, the obtained IAS estimates are compared to the public results on the same data set as provided by [8]. In [8], there are 6 other vibration-based IAS estimation techniques that provide accurate IAS profiles and enable a qualitative accuracy assessment. Figure 2 displays a zoom of the 8 estimated speed profiles along with the encoder around a critical part of the speed profile, namely right before the large run-up.

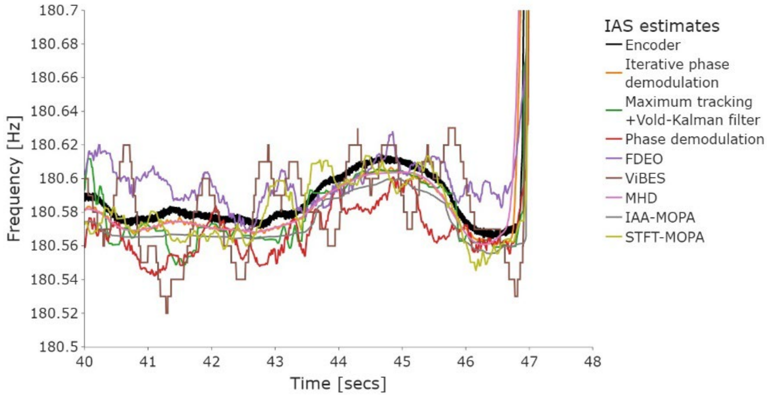

Figure 2: Comparison of the estimated instantaneous angular speed profiles, zoomed right before the sudden run-up.

Since visual accuracy assessment based on Fig. 2 is difficult, the error between the reference encoder speed and the estimated speeds is calculated. Figure 3 shows a waterfall plot of the absolute error profiles on the same scale to give the reader an idea of the shape of the error profiles. No axis tick labels are shown due to the offsets used to improve the visualisation. One notable source of estimation error for all 8 methods is at the very start of the run-up as shown in Fig. 1, showcased by the large error peaks in Fig. 3.

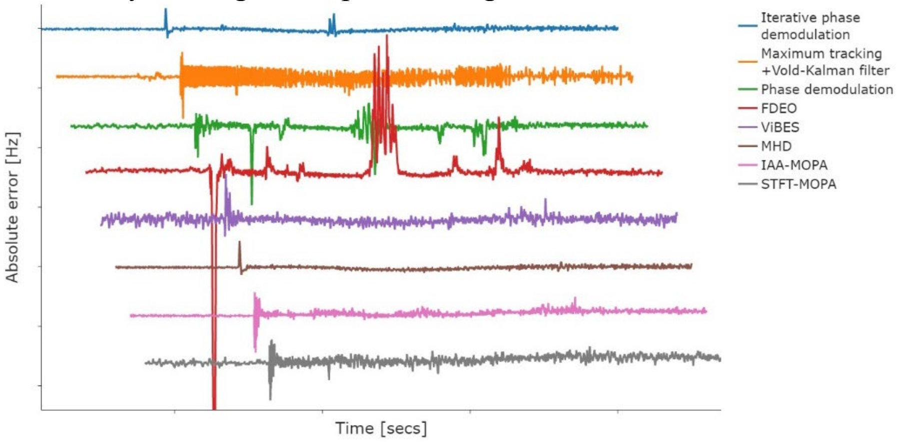

Figure 3: Absolute error profiles of 8 different state-of-the-art instantaneous angular speed estimation techniques on the Surveillance 8 aircraft gearbox data.

To give a more quantitive insight into the performance of the ST-IAA-based MOPA compared to the STFT-based MOPA, Fig. 4 shows the mean and median absolute errors of the 8 different methods, ranked from left to right based on the median absolute error. Based on Fig. 4, it can be concluded that the ST-IAA-based MOPA has an almost 40% reduction in both mean and median absolute error compared to the STFT-based MOPA. Using the ST-IAA puts MOPA on par with the best performing harmonic phase demodulation approaches, which benefit significantly from the very high SNR of the HP shaft gear mesh harmonics and the lack of interfering harmonics in the chosen filter bandwidth around those harmonics. These last two phenomena are quite uncommon in complex machinery making MOPA a more versatile and reliable tool typically to tackle IAS estimation problems. The fact that the ST-IAA-MOPA achieves a similar accuracy to these demodulation approaches on a dataset that is particularly well-suited for the latter, is very promising with regard to its general applicability.

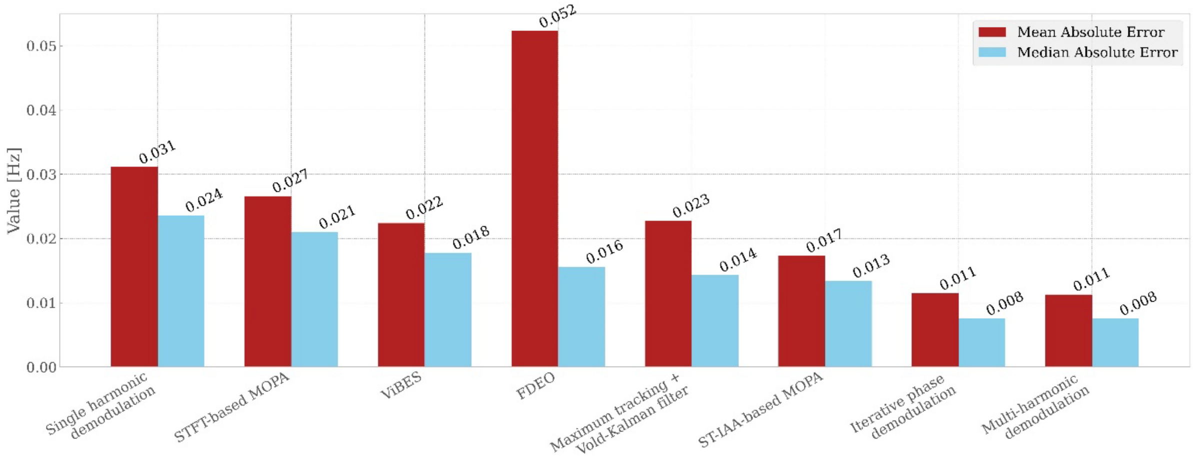

Figure 4: Mean and median absolute errors for every method on the Surveillance 8 data using the encoder as reference.

Conclusions

This paper investigated the short-time iterative adaptive approach (ST-IAA) as an improved time-frequency representation input for the multi-order probabilistic approach (MOPA) as compared to the short-time Fourier transform (STFT). Performance analysis of both the STFT- and ST-IAA-based MOPA on vibrations measured on an aircraft engine gearbox confirm that using the ST-IAA instead of the STFT as an input for MOPA can significantly improve the instantaneous rotating speed estimation accuracy while not having to change any input parameters or do any additional hyperparameter fine-tuning.

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References

1. M. J. Shensa et al., "The discrete wavelet transform: wedding the a trous and mallat algorithms," IEEE Transactions on signal processing, vol. 40, no. 10, pp. 2464–2482, 1992.
2. B. Barkat and B. Boashash, "Design of higher order polynomial wigner-ville distributions," IEEE Transactions on Signal Processing, vol. 47, no. 9, pp. 2608–2611, 1999.
3. M. Greitans, "Adaptive stft-like time-frequency analysis from arbitrary distributed signal samples," in International Workshop on Sampling Theory and Application, Samsun, Turkey, 2005.
4. T. J. Gardner and M. O. Magnasco, "Sparse time-frequency representations," Proceedings of the National Academy of Sciences, vol. 103, no. 16, pp. 6094–6099, 2006.
5. Y. Wang, "Seismic time-frequency spectral decomposition by matching pursuit," Geophysics, vol. 72, no. 1, pp. V13–V20, 2007.
6. Y. Wang and J. Orchard, "Fast discrete orthonormal stockwell transform," SIAM Journal on Scientific Computing, vol. 31, no. 5, pp. 4000–4012, 2009.
7. Q. Leclere, H. Andre, and J. Antoni, "A multi-order probabilistic approach for instantaneous angular speed tracking debriefing of the cmmno 14 diagnosis contest," Mechanical Systems and Signal Processing, vol. 81, pp. 375–386, 2016
8. C. Peeters, Q. Leclere, J. Antoni, P. Lindahl, J. Donnal, S. Leeb, and J. Helsen, "Review and comparison of tacholess instantaneous speed estimation methods on experimental vibration data," Mechanical Systems and Signal Processing, vol. 129, pp. 407–436, 2019.
9. C. Peeters, Q. Leclere, J. Antoni, P. Guillaume, and J. Helsen, "Vibration-based angular speed estimation for multi-stage wind turbine gearboxes," in Journal of Physics: Conference Series, vol. 842, no. 1. IOP Publishing, 2017, p. 012053.
10. C. Peeters, J. Antoni, Q. Leclere, T. Verstraeten, and J. Helsen, "Multi-harmonic phase demodulation method for instantaneous angular speed estimation using harmonic weighting," Mechanical Systems and Signal Processing, vol. 167, p. 108533, 2022.
11. C. Peeters, A. Jakobsson, J. Antoni, and J. Helsen. "Improved time-frequency representation for non-stationary vibrations of slow rotating machinery." In PHM Society European Conference, vol. 7, no. 1, pp. 401-409, 2022.
12. T. Yardibi, J. Li, P. Stoica, M. Xue, and A. B. Baggeroer, "Source localization and sensing" IEEE Transactions on Aerospace and Electronic Systems, vol. 46, no. 1, pp. 425–443, 2010.
13. G.-O. Glentis and A. Jakobsson, "Superfast approximative implementation of the iaa spectral estimate," IEEE Transactions on Signal Processing, vol. 60, no. 1, pp. 472–478, 2011
14. J.Antoni,J.Griaton, H. Andre, L. D. Avendan~o-Valencia, F. Bonnardot, O. Cardona-Morales, G. Castellanos-Dominguez, A. P. Daga, Q. Leclere, C. M. Vicuna, et al., Feedback on the surveillance 8 challenge: vibration-based diagnosis of a safran aircraft engine, Mechanical Systems and Signal Processing 97 (2017) 112{144}.