EVENT ALIGNMENT, WARPING BETWEEN RUNNING SPEEDS

Niels Henrik Pontoppidan[1] and Ryan Douglas[2]

[1]Informatics and Mathematical Modelling, Richard Petersens Plads 321, Technical University of Denmark, 2800 Lyngby, Denmark. nhp@imm.dtu.dk, Tel +45 4525 3899, Fax +45 4587 2599
[2]Dept. of Mechanical & Chemical Engineering, Heriot-Watt University, Riccarton, EH14 4AS, Edinburgh, United Kingdom. r.douglas@hw.ac.uk, Tel +44 131 451 4569, Fax +44 131 451 3129

ABSTRACT

We are pursuing a system that monitors the engine condition under multiple load settings, i.e. under non-stationary operating conditions. We have obtained data from the electronically controlled 2-stroke engine at MAN B&W Research Copenhagen. The running speed when data acquired under simulated marine conditions (different load settings on the propeller curve) was in the range from 60 to 120 rotations per minute; furthermore the running speed was stable within periods of fixed load.
Electronically controlled engines can change the angular timing of certain events, such as fuel injection in order to optimize its performance. However this behaviour inhibits our framework presented in COMADEM 2003 from detecting condition changes across those load changes.
This paper evaluates different methods that align acoustic emission signals observed under different load settings. We evaluate the methods on data from the fuel injection period where the largest deviations in timing occur.
The idea is that we, given aligned data, can use the already developed component analysis framework for non-stationary monitoring of condition changes. It should further be noticed that the proposed warp framework also enables alignment across cylinders and engines.

KEYWORDS

Event alignment, signal processing, non-stationary condition monitoring, acoustic emission.

INTRODUCTION

We have obtained acoustic emission (AE) RMS signals from the cylinder liner and cover of the electronically controlled 2-stroke at MAN B&W Research Copenhagen. During the acquisition the running speed was in the range 60-120 rotations per minute. Further the running speed was virtually constant during periods of constant load settings.
Up to now research has mainly focused on condition monitoring under fixed operational conditions, see further [1], [2] and [6]. We are currently pursuing non-stationary condition monitoring, i.e. condition monitoring under different load settings that should resemble realistic marine conditions.
Electronically controlled engines can change the angular timing of certain events, such as fuel injection in order to optimize its performance. However this behaviour inhibits our framework presented in COMADEM 2003 [1] from detecting condition changes across those load changes. The result is a false alarm triggered by the condition change. Also mechanically controlled engines display such variations,

due to the fact that some events have fixed length in time and some in angular "time", thus it is not sufficient to use the crank angular domain as described in [3] to overcome this problem.
Joint research in the AE-WATT project has revealed a stable functional dependence in the observed AE signals w.r.t. running speed/load, which this paper exploits in order to compare AE signals observed under different load settings. We expect to add this novel tool to our component analysis framework [1] enabling non-stationary condition monitoring.

Timing changes during injection period

The three events depicted in Figure 1 are believed to arise from mechanical interaction between the injector spindles and their respective stops within the injector, with fuel delivery occurring between the second and third peaks. The process is partly mechanically controlled by pre-set spring pressure and electronically controlled since the fuel flow to the injector is electronically controlled.
In order to meet the increased load the engine response is to inject more fuel. This is achieved by prolonging the fuel delivery period with consequential retarded closure of the injector. Since the AE directly reflects the mechanical operations within the injector the increased fuel injection duration is readily identifiable.
Just as the engine changes the timing of the events, we are going to undo those changes. Figure 1 shows meaned injection period signals at three different loads on the propeller curve. All loads have been annotated with a set of event landmarks. The following sections describe the applied method and end up with the alignment of the 50% and 25% load data.

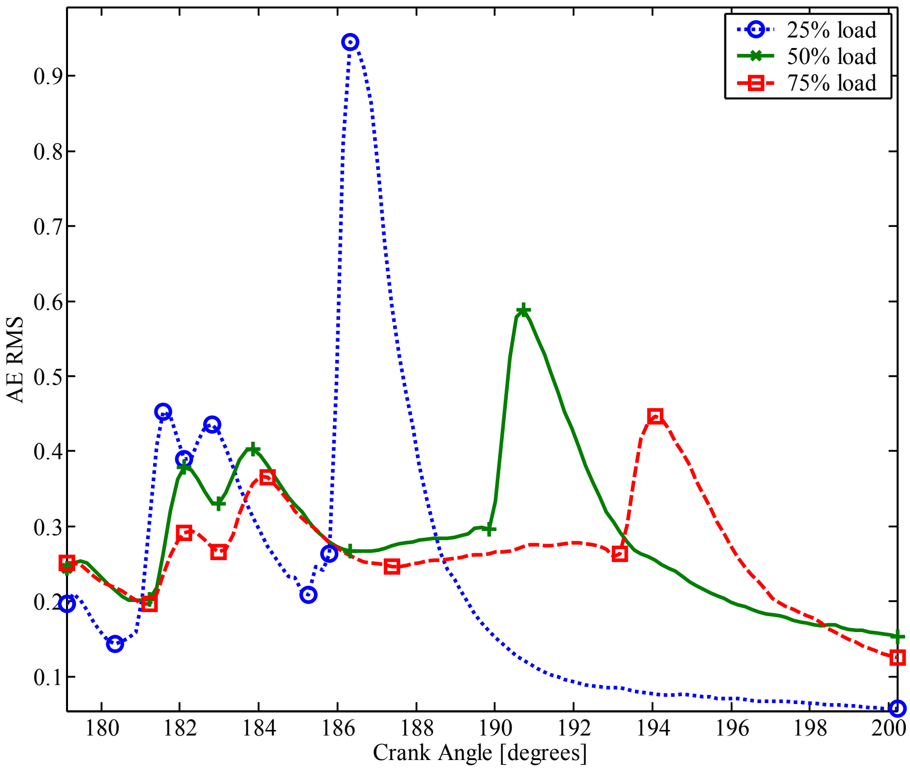

Figure 1: Mean Acoustic emission signals during injection period with different load settings. The markers show the time position of the landmarks that should be aligned.

METHODOLOGY

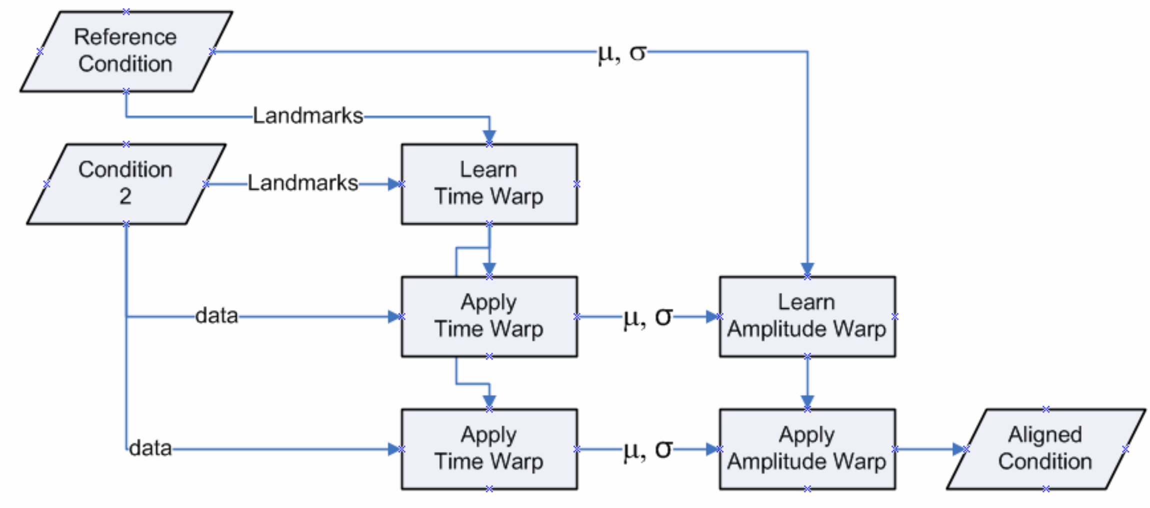

Figure 2: Outline of event alignment algorithm

Equation 1 and 2 define the warping of the observed signal $x_2[n]$ into the aligned signal $x_A[n]$. The first step is applying the time-warp function f(), i.e., a function that aligns the landmarks and events of the two conditions in time. This possibly leaves amplitude mismatch which is resolved by subtracting the "other condition" mean $\mu_2[n]$, followed by compression of variance g[n], ending with addition of the reference mean $\mu_R[n]$ (see step 1-3 in figure 2).

$$x_A[n] = \left(f(x_2[n]) - \mu_2[n]\right) g[n] + \mu_R[n] \tag{1}$$

$$g[n] = \begin{cases} 1 & \sigma_2[n] > \sigma_R[n] \\ \sigma_2[n] \big/ \sigma_E[n] & \sigma_2[n] \le \sigma_R[n] \end{cases} \tag{2}$$

We use data to learn the parameters of the event alignment. In order to ensure generability of the algorithm we obtain individual subsets for the learning of each function, i.e. we randomly select some examples that we learn the respective landmarks from, another set for the respective mean-signals and yet another set for the variance.

Warp path

The function f() describes the warp-path[10], i.e. a time-stretching function. An example of a warp path is shown in Figure 3. The local slopes correspond to the necessary local (reciprocal) time-stretching. Depending on how the warp path is obtained a set of constraints can be defined, e.g. not allowing negative slope etc. The dark rhomb in the figure is the Itakura-parallelogram[8], which is one of normally applied constraints. We have applied another constraint namely the landmarks, which we obtain from analysing the engine. Simply if f() aligns the landmarks it also aligns the signals..

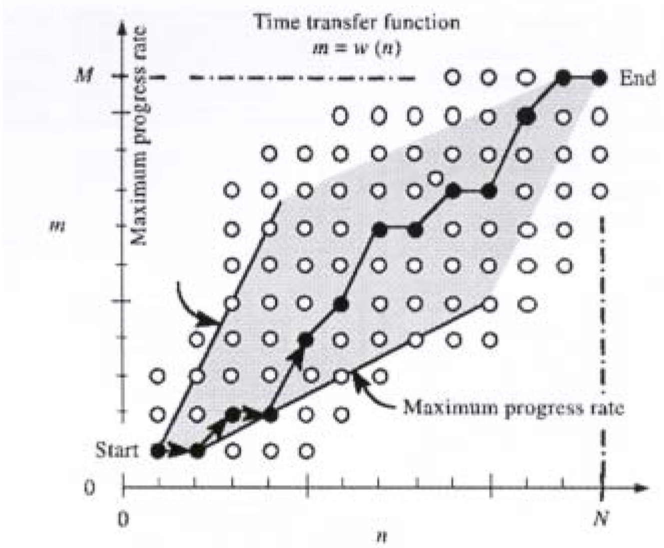

Figure 3: A warp path. Figure due to Leonard et al. [10]. The local slopes correspond to the necessary local (reciprocal) time-stretching.

Dynamic Time Warping based on Phase Vocoder Techniques

Dynamic Time Warping (DTW) has successfully been applied to alignment of speech segments [4]. In DTW the actual time alignment is performed using Phase Vocoders [9]. The Phase Vocoder (PV) alters the time duration of a sequence whilst keeping the frequency information literally unchanged[5], i.e., playing speech at a faster rate without the well known chip-monk effect. However for alignment of signals in a component analysis based framework as ours, the artefact of spurious peaks is problematic. What happens is that the PV in some cases repeats or skips frames of observed signal, possibly removing or repeating the, for us important events. Thus using DTW for the functional form of f() in Eqn. (1) was abandoned.

Spline interpolation in time domain

By allowing changes in the frequency content can use spline-interpolation in the time-domain. We have tested 2 types of splines, piecewise linear (1^{st} order) and cubic (3^{rd} order) splines. In many cases the cubic interpolation is better, as the derivatives of the warp-path are continuous. This means that the time-stretch at the landmarks is smoother. Sometimes, especially if landmarks are close to each other, cubic interpolation can lead to negative slope. This is an issue that we will have to investigate further, most likely ending up with a constrained regression scheme.

Amplitude warp

The function g[n] is only allowed to compress variance, since we cannot determine the source of the observed variance. Is the observed variance due to mode variation or measurement noise? Indeed amplification of measurement noise would be wrong. In experiments with unconstrained g[n] we observed that amplification of measurement noise lead to negative values – remember the observed signals are non-negative RMS signals. On the other side the constraint also keep the variance after alignment lower or equal to the variance in the un-aligned data, thus the aligned examples seem more "normal" than the un-aligned; this is called over-fitting an important issue that we will investigate further.

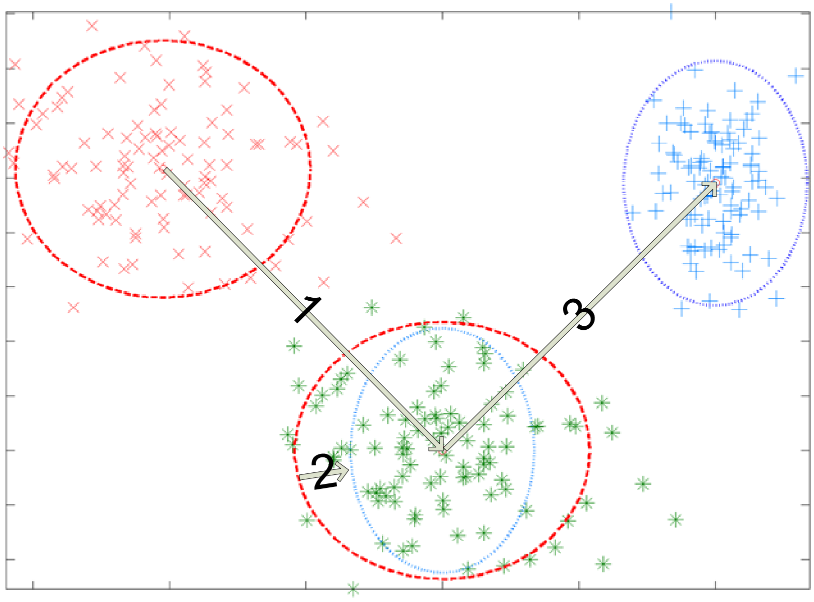

Figure 4: Example of amplitude warp. Samples from a two-dimensional i.i.d. Gaussian are translated, scaled and translated, i.e., removing mode mean, re-scaling variance and adding reference mean.

Example of event alignment

Figure 5, Figure 6 and Figure 7 show how 50% load data is event alignment into resembling 25% load data. Figure 5 show the data after time-stretching, as expected the landmarks, peaks and valleys are aligned but we notice the prominent amplitude mismatch. Figure 6 shows the data means after amplitude warp – they are identical. Notice that this is even though another set of examples was used to learn the parameters as Figure 2 indicate. Figure 7 displays the result of applying the event alignment to a set of 50% load examples, again another set of examples was used to learn the parameters.

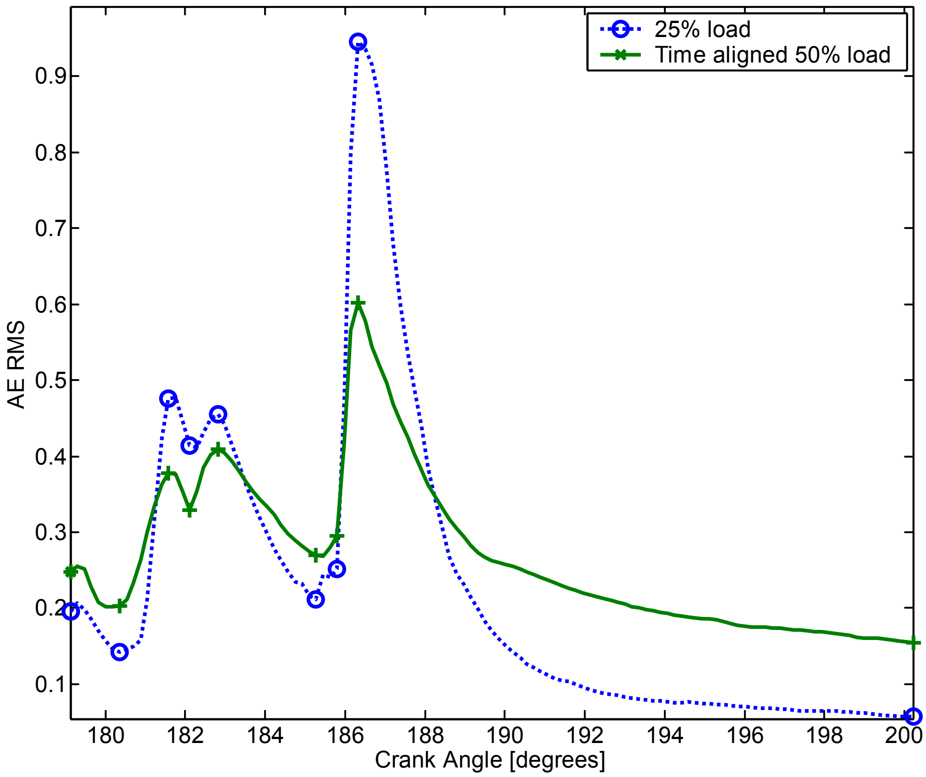

Figure 5: Amplitude mismatch after time warp. The two displayed signals are meaned over 30 cycles.

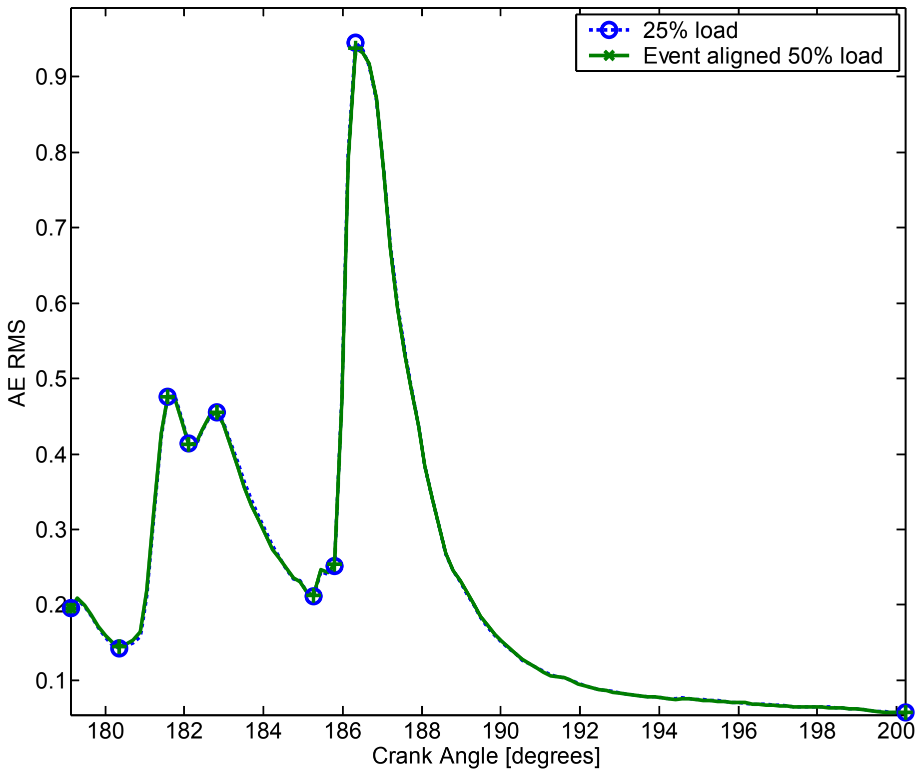

Figure 6: The event alignment provides a perfect match of the mean signals of 25% load data and aligned 50% data.

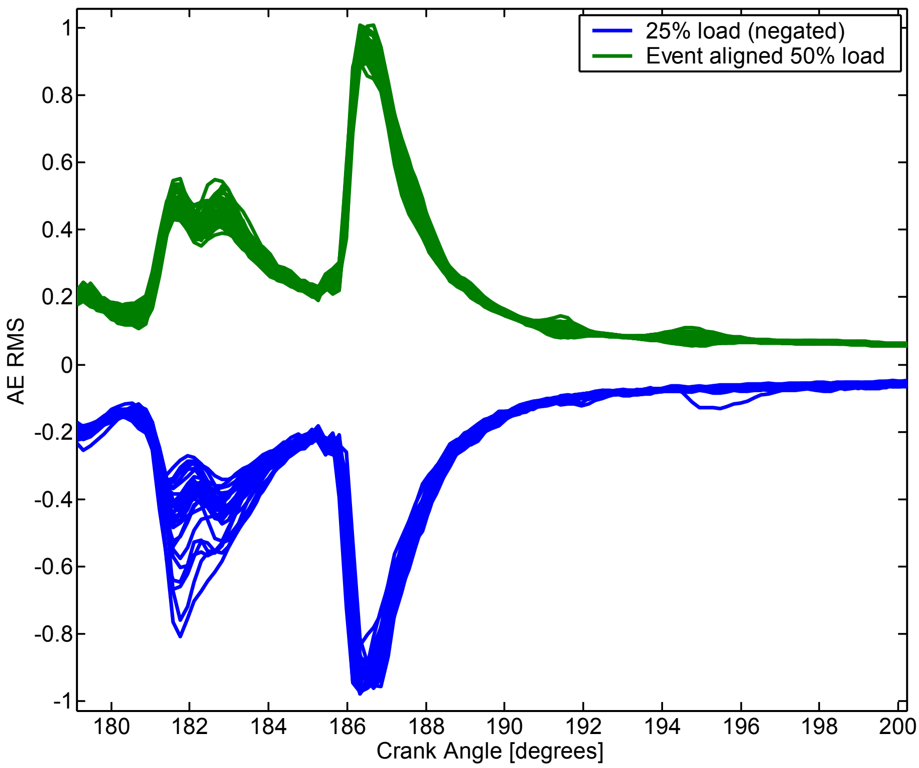

Figure 7: Examples of negated 25% load data and 50% load data. Notice the lesser amount of variance around 182° in the aligned data.

CONCLUSION

We have demonstrated how knowledge of engine evens can be used to turn data acquired under one operational condition into resembling another also known condition. We believe that this approach enables condition monitoring across known condition changes and thus enables non-stationary condition monitoring. Non-stationarity is a key component in our research for reliable condition monitoring under marine conditions, and we will continue this research and conduct the necessary experiments with full cycle data that demonstrate the non-stationary behaviour of the whole condition monitoring system. Another line of work is automatic identification of events where our research indicates that other sensor positions, namely close to the injector could provide better resolution w.r.t. events.

ACKNOWLEDGEMENTS

The work is supported by EU Competitive and Sustainable Growth Programme GRD2-2001-50014 – the AE-WATT project. Data was provided by MAN B&W Diesel A/S. Discussions with other project partners was very appreciated.

REFERENCES

[1] Pontoppidan, N. H., Larsen, J., Fog, T., "Independent component analysis for detection of condition changes in large diesels" in COMADEM 2003, no. 16, pp. 493-502, 2003.

[2] G. Chandroth, A. Sharkey and N. Sharkey, "Vibration signatures, wavelets and principal components analysis in diesel engine diagnostics" in Marine Technology ODRA 99, Oct. 1999.

[3] G. Chandroth and A. Sharkey. Utilising the rotational motion of machinery in a high resolution data acquisition system. In Proc of Computers and ships- from ship design and build, through automation and management and on to ship support, May 1999.

[4] D. Ellis, "Dynamic Time Warp (DTW) in Matlab", htpp://labrosa.ee.columbia.edu/matlab/dtw.

[5] J. Flanagan and R. Golden, "Phase Vocoder", Bell System Technical Journal, pp. 1493-1509, Nov. 1966.

[6] T. Fog, L. Hansen, J. Larsen, H. Hansen, L. Madsen, P. Sørensen, E. Hansen and P. Pedersen, "On Condition Monitoring of Exhaust Valves in Marine Diesel Engines," in Y. H. Hu, J. Larsen, E. Wilson and S. Douglas (eds.), Proceedings of the IEEE Workshop on Neural Networks for Signal Processing IX, IEEE, Piscataway, New Jersey, 1999, pp. 225–234.

[7] A. Frances, J. Gill, J. Reuben and J. Steel, "A Study of the Variability of Acoustic Emission Signals from a Medium Size Marine Diesel Engine under Service Conditions," in O. P. Shrivastav, B. Al-Najjar and R. B. Rao (eds.), COMADEM 2003, COMADEM International, 2003, pp. 503–512.

[8] E. Keogh, "Exact Indexing of Dynamic Time Warping," in Proceedings of the 28th VLDB Conference, Hong Kong, China, 2002.

[9] J. Laroche, "Time and Pitch scale modification of audio signals" in "Applications of digital signal preprocessing to audio and acoustics", Mark Kahrs and Karlheinz Brandenburg (eds.), Kluwer Academic Publishers, March 1998.

[10] Francois Leonard, Marc Foata, and Jean-Yves Paquin. Vibro-acoustic signature comparison and time-warping correction with multi-scale correlation. Mechanical Systems and Signal Processing, 14(3):443–458, 2000.