BLIND SEPARATION OF MACHINE VIBRATION WITH BILINEAR FORMS

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ABSTRACT

We propose the use of blind source separation to enhance the fault-related machine component in a multichannel measurement. The feasibility of this approach is demonstrated in two real-world applications. For source separation we use the *bilinear forms* framework, which allows the combination of several (problem-specific) separation criteria. In experiments with artificial data we show that the best performance with either criterion can be approximated by using their combination.

1. INTRODUCTION

Fault-related machine vibration is usually corrupted with structural machine vibration and noise from interfering machinery. Moreover, measurements may show large deviations in noise contribution if the sensor mounting position is varied. In rotating machines there will always be vibration present: no machine is perfectly balanced and small structural imperfections (contacts, wear, etc.) will induce forced vibrations in the structure. Certain components (like gearboxes in the meshing process) are inherently generating shock pulses, leading to the excitation of machine resonances. The excitation source is usually the interesting signal, but the measurement from a sensor mounted on the casing will exhibit a (possibly convoluted and) mixed version of the sources with other structural vibration superposed on it [1]. Moreover, in the presence of nearby non-isolated machines (as often in ship engine rooms), severe interference may be present in the measurements as well. Many well-known techniques from signal processing have been applied to this problem in the past. They rely either on detailed knowledge about the type of source that is to be identified (e.g. an impulsive excitation, as with bearing failures) or on the identification of the transmission characteristic (in a modal analysis). Taking a *blind* approach, one may try to identify (an approximation to) the (local) transmission characteristic using only sensor measurements and general characteristics of the supposed source signals.

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2. SEPARATING MACHINE VIBRATION

In this paper we assume that the mixing process is linear and instantaneous, hence we approximate the influence of the transmission from source to sensor with a single tap filter with zero time delay. In previous work [2, 3] separation of the underlying sources in vibro-acoustical systems was studied using a singular value decomposition of the cross-spectral matrix or using modal and eigenvector beamformers [4]. In [5] it was concluded that the instantaneous mixing model did not hold for the machine under consideration. Supposedly, this is related to the rigidity and size of the structure under investigation: large and elastic structures will account for severe filtering and delays in the transmission from source to sensor, whereas small and rigid structures may show mixing that is approximately instantaneous [6]. Second, the abundance of knowledge about vibration that is emitted by rotating machines [1] should preferably be used in the separation procedure. We can either use general assumptions on the second-order temporal structure of the signals [7, 8, 9] for this purpose or take a maximum likelihood approach, e.g. by fitting the underlying signal distributions or use parametric models of machine vibration. We will only study the first approach in this paper.

Consider the case in which one has access to multiple measurements $\mathbf{x}$ of a mixture of independent signals $\mathbf{s}$. Assuming a linear mixing model A and allowing additive noise $\mathbf{v}$ leads to the model

$$\mathbf{x} = A\mathbf{s} + \mathbf{v} \quad (1)$$

where boldface variables denote random vectors with zero mean and finite covariance. Moreover, $\mathbf{s}$ has statistically independent components. The problem of ICA is now: given T realizations of $\mathbf{x}$, estimate both mixing matrix A and the independent components $\mathbf{x}$. The *algebraic approach* [10] to ICA uses the fact that, after spatial prewhitening, the ICA-basis is given by a rotation of the (whitened) measurements. It was shown [11, 12] that this approach is robust against noise due to measurement errors and finite sample sizes. One can use second-order *temporal* correlations in data by choosing the "stack" of eigenmatrices to be diagonalized as the instantaneous spatial correlation matrix and a set of time-lagged spatial correlation matrices. The performance depends on the choice of time lags [7], but it was shown that just taking *several* time lags into account is often sufficient for achieving separation [12]. However, taking noninformative delays into account may lead to numerical problems in the diagonalization procedure, hence decreasing the performance. This approach can be extended by considering the time-frequency characteristic of the sources. The stack of matrices that is to be diagonalized can now be constructed from a set of 'second-order similarity' matrices obtained in several frequency bands at several time stamps. Hence, nonstationarity of the sources can be used for the separation [13].

3. SOURCE SEPARATION WITH BILINEAR FORMS

The time-frequency algorithm can be looked upon as a special case of the bilinear forms based separation algorithm by Leshem [8], where the employed time-frequency distribution is a just a particular kind of *bilinear form* (a kind of "generalized second-order similarity measure"). Here, we define a bilinear form g to be *separating* mixtures $y_1, ..., y_d$ into sources $s_1, ..., s_d$ if

$$g(s_k, s_l) = c_k \delta_{kl}, 1 \leq k, l \leq d \quad (2)$$

where δ_{kl} is the Kronecker delta and c_k is nonzero for all k. A bilinear form is represented by a "similarity matrix"

$$R_g^{yy} = \begin{bmatrix} g(y_1, y_1) & \dots & g(y_1, y_d) \\ \dots & \dots & \dots \\ g(y_d, y_1) & \dots & g(y_d, y_d) \end{bmatrix} \quad (3)$$

in the basis of mixtures $y_1, ..., y_d$. Now several bilinear form that are *separating* represent a set of similarity matrices that can be treated in a joint diagonalization procedure in the same manner as the eigenmatrices in the JADE and SOBI algorithms [7, 10]. This more general formulation allows the incorporation of traditional separation algorithms, depending on the choice of bilinear form. The simplest bilinear form is

$$g_0(x, y) = \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{\infty} x(i)^* \cdot y(i) \quad (4)$$

which is just the inner product between the two vectors x and y. When we 'plug-in' this form into a separation algorithm, we end up with PCA or spatial prewhitening. Other choices for g can be

$$g_i(x, y) = \lim_{N \to \infty} \frac{1}{N} \sum_{t=0}^{N} x(t)^* \cdot y(t - \tau_i) \quad (5)$$

leading to the SOBI algorithm [7]. Choosing

$$g_{\tau,\alpha}(x, y) = \lim_{N \to \infty} \frac{1}{N} \sum_{t=0}^{N} x(t)^* \cdot y(t - \tau) e^{-2\pi j \alpha t} \quad (6)$$

leads to an algorithm in which sources with different cyclostationary characteristics can be separated. This exploitation of the *spectral redundancy* in a source is similar to the way that the *phase-SCORE* algorithm [14] separates sources. The choice

$$g_{t,f}(x, y) = \sum_{m,l \in \mathcal{Z}} \phi(m, l) x(t+m+l)^* y(t+m-l) e^{-4\pi j f l} \quad (7)$$

for various time-frequency "atoms" (t, f) and certain choice of the smoothing kernel $\phi(m, l)$ leads to the time-frequency algorithm of Belouchrani [13]. The choice of time-frequency atoms to include determines the number of matrices to diagonalize. If this number becomes too large or the matrices are largely uninformative, this will lead to an intractable or suboptimal diagonalization procedure. Hence, one can take only a subset of these matrices into account, representing the time-frequency atoms with the highest energy. Moreover, the proper choice of spectral and temporal resolution seems critical for successful separation. This is based on experiences with a set of mixed calibration signals with different time-frequency characteristics (1 linear chirp, 2 Gaussian AM linear chirps, 2 signals with (different) Doppler-shift and 1 sinusoidal AM linear chirp), figure 1. In our further experiments with time-frequency separation we choose a Wigner-Ville distribution as bilinear form, which corresponds to a smoothing kernel identically 1. The time-frequency algorithm has a tendency to concentrate signal power and disperse noise power by choosing suitable time-frequency atoms.

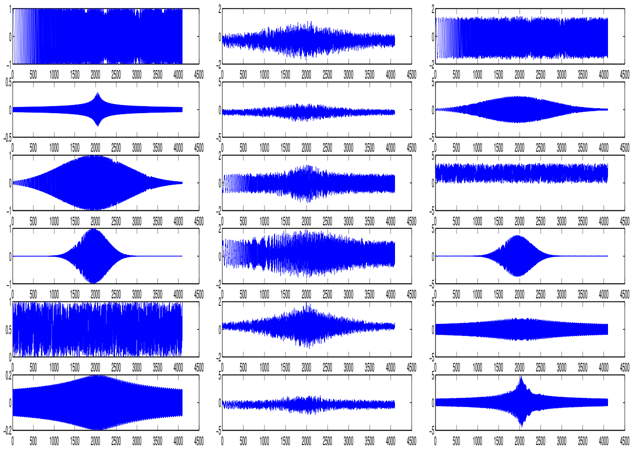

Figure 1: Sources(a), mixtures (b) and reconstructed sources (c) with time-frequency characteristics

4. COMBINING SEPARATION CRITERIA

It is known [15] that once-per-rotation pulses of noise due to e.g. a bearing fault can be modelled as band-limited noise modulated with a periodic rectangular pulse, which is a signal that exhibits cyclostationarity. Hence we generated an analytic AR(1)-source [7], which was modulated with a carrier at (normalized) frequency f_0. This type of signal exhibits cyclostationarity at cyclic frequency $\alpha = 2f_0$, since the signal is (conjugate) self-coherent with a $2f_0$ frequency-shifted version of its complex conjugate [14]. The self-coherence of a cyclostationary signal (with $f_0 = 0.4$) as a function of the frequency-shift that is applied to the signal's conjugate is shown in figure 2. Clear peaks in the self-coherence are present at a shift of $2f_0$, but a small deviation results in pronounced loss of coherence. This indicates that separation algorithms that use this criterion may be very sensitive to the choice of the (correct) cyclic frequency.

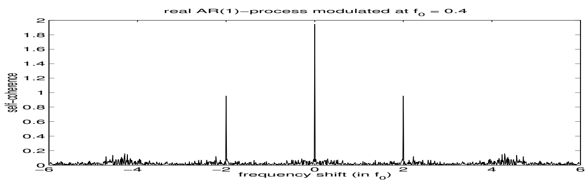

Figure 2: Self-coherence as a function of frequency-shift

We mixed two cyclostationary sources, i.e. two complex modulated analytic AR(1)-sources with random initial phase, impinging on a sensor array with angles -12 and 13 degrees. Apart from direction, the source signals only differ w.r.t. their modulation frequency $f_1 = f_0 + \Delta f$. We compare the results obtained with SOBI, SCORE and a combination of both methods, if we vary the frequency shift Δf.

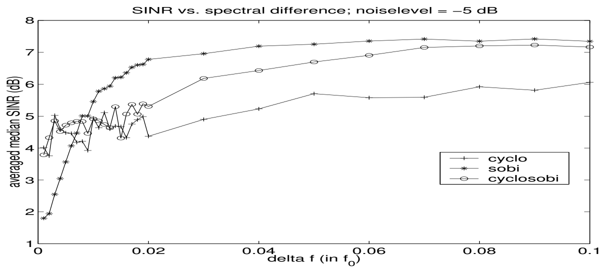

Figure 3: Average median SNR vs. δf for SOBI, SCORE and their combination, -5 dB SNR

We repeat 250 runs of the source separation algorithm (SOBI, SCORE or their combination), and the median SINRs (in dB), averaged for both sources, are computed. In both SOBI and SCORE we used 5 similarity matrices (hence 10 matrices in the combination algorithm). In figures 3 and 4 the results are plotted for source SNRs of -5 and 25 dB, respectively.

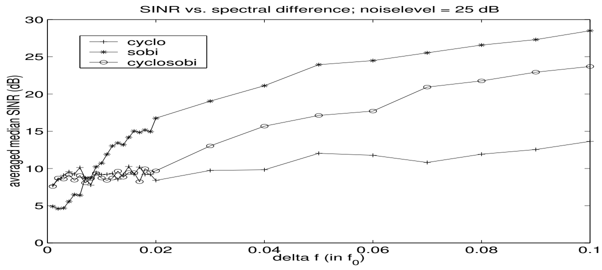

Figure 4: Average median SNR vs. δf for SOBI, SCORE and their combination, 25 dB SNR

It can be seen that for small spectral difference, only SCORE will be able to do the separation. For larger spectral difference ($\delta f > 0.01$) there is enough information in the lagged covariance matrices, so SOBI performs best. The combination algorithm follows the better performance of both methods: for small spectral shift it behaves like SCORE, whereas for larger shifts it approaches SOBI. This effect is strongest for low source SNRs. We noticed a large variation in 250 repetitions of an experiment. In order to quantify this, we determined the cumulative density of the SINRs in 250 repetitions for the first source (the second source shows similar behaviour). In figure 5 the densities for small and large spectral shift ($\Delta f = (0.001, 0.1)$) are shown for SOBI, SCORE and their combination separately. For small shift the combination behaves like SCORE, whereas for large shift it behaves like SOBI.

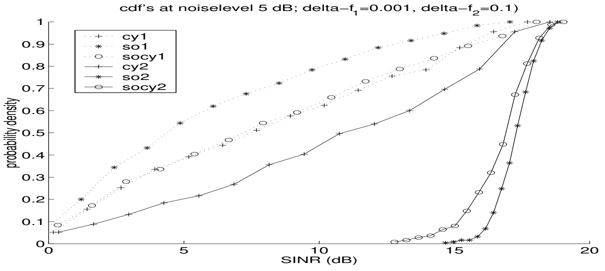

Figure 5: Cdf of SINRs, 5 dB SNR

In both cases it follows the maximum performance. If we repeat the previous experiments using only 1 time delay, we see that the combination algorithm lags behind SOBI for large spectral shifts, whereas it performs still optimal for small shifts (figure 6).

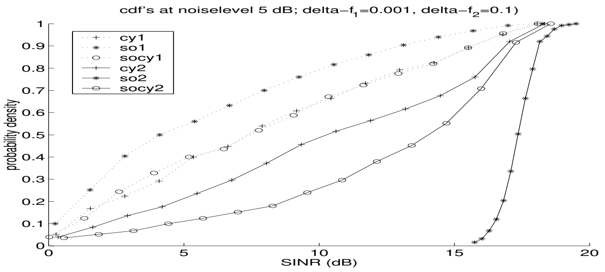

Figure 6: Cdf of SINRs, 5 dB SNR; 1 delay

5. ROTATING MACHINES APPLICATION

5.1. Vibrational artifact removal

In the first case study vibration was measured on a pumpset in a pumping station, in which a severe gearbox failure was present [16]. Mounted onto the gearbox-casing was a small oil pump that was running at 285 Hz. In most of the measurements obtained with 4 accelerometers distributed on the casing of the machine and the oil pump this interference was visible (figure 7(a)). The signals were downsampled to approx. 400 Hz and the signal subspace contained 3 components (figure 7(b)). After performing time-frequency ICA on the multichannel measurement (spectral resolution in algorithm was 1024 bins and 50 most energetic atoms were used), a decomposition into (nearly) temporally uncorrelated components was obtained (figure 7(c)). The first component consists mainly of the oil pump frequency, whereas the second component contains predominantly other vibration of the oil pump (that was not measured on the machine). The third component contains mainly the gear-mesh frequency (216 Hz) of the machine, which was high due to the gearbox fault. This component was measured on the oil pump as well (figure 7a, 4th channel), but suppressed in the 'cleansed' oil pump measurement (figure 7c, 2nd channel). Prewhitening is clearly insufficient for source separation (figure 7b), since the peaks at 216, 285 and around 100 Hz are present in all three components. We noticed that proper choice of frequency band and time shift was critical for the performance of the algorithm: bad choices didn't allow for significant improvement over PCA. In our investigation, the use of 50 atoms with sufficient spectral resolution was adequate for achieving source separation.

5.2. Acoustical separation of rotating machines

In the second case study, noise from a passing car was measured on a 5-microphone array. Severe disturbances were present, like a rotating machine running stationary around 60 Hz, an airplane crossing the scene and wind bursts from vegetation in the vicinity of the array. The measurements were lowpass-filtered, so the main signals present were wind, car and machine noise. Prior to processing, the signals were time-aligned using cross-correlation between the sensors. The time-frequency plot of a typical measurement is shown in figure 9(a). The spectra corresponding to these measurements are shown in figure 8(a). After prewhitening we obtained the spectra in figure 8(b). Since one of the sources is moving (the car), we can take the nonstationarity of the signal due to this source into account. We applied the time-frequency algorithm of (7) to the measurements (using 50 matrices that represent the most energetic tf-atoms), where the signals were downsampled to plm. 200 Hz and the time-frequency atoms had a width of 50 time samples and approx. 1.5 Hz (which was sufficient for assuming narrowband sources). This resulted in the spectra of figure 8(c). The rotating machine is separated into the fifth component, its time-frequency behaviour is plotted in figure 9(b). The rotating machine (stationary component around 60 Hz) was not visible in the time-frequency plots of the measurements (figure 9(a)). Moreover, the second component is predominantly a wind - component and the first component contains the car (figures 8(c) and 10(a). A drawback of the time-frequency algorithm is shown in components 3 and 4 and figure 10(b): the number of underlying sources was three, but since we forced a solution into 5 components with distinct time-frequency behaviour (according to the most energetic time-frequency descriptors), the car signature is split into two parts.

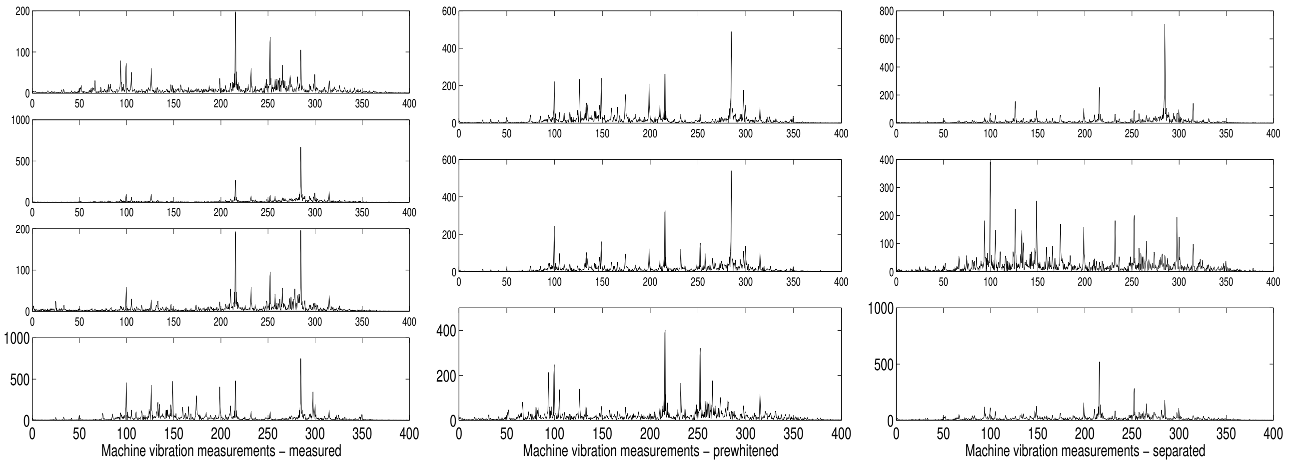

Figure 7: Spectra of vibration measurements (a), prewhitened (b) and separated components (c)

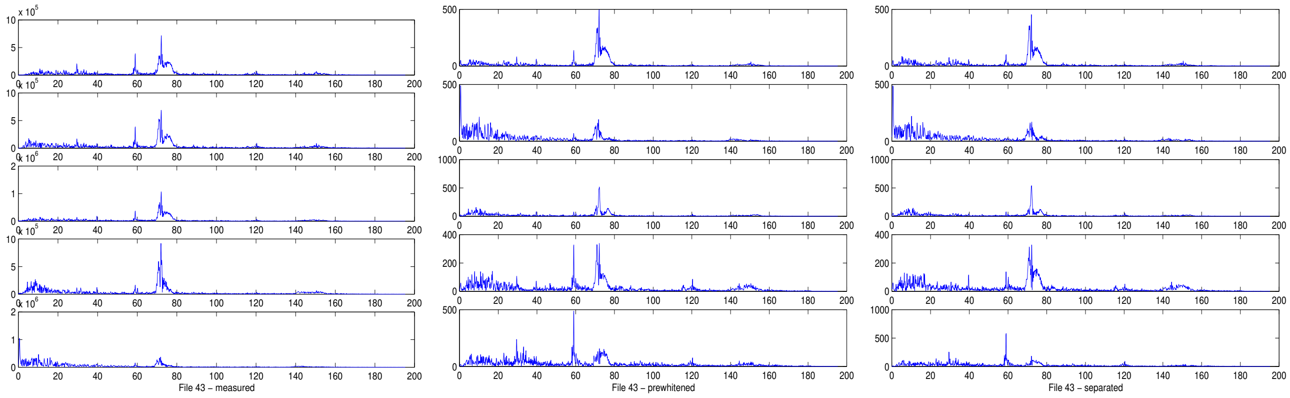

Figure 8: Spectra of acoustical measurements (a), prewhitened (b), and separated components (c)

6. CONCLUSION

We showed that using the bilinear forms framework it is possible to include several separation criteria into a source separation algorithm. This can be beneficial for mixtures exhibiting several kinds of structure, where it is a priori not clear under which conditions each criterion is useful. Specifically, it allows the use of particular information that can be relevant for source separation in rotating machine applications, like cyclostationarity and time-frequency information. This was demonstrated for both acoustical and vibrational monitoring of rotating machines, where the relevant machine component could be separated out of a set of measurements.

7. REFERENCES

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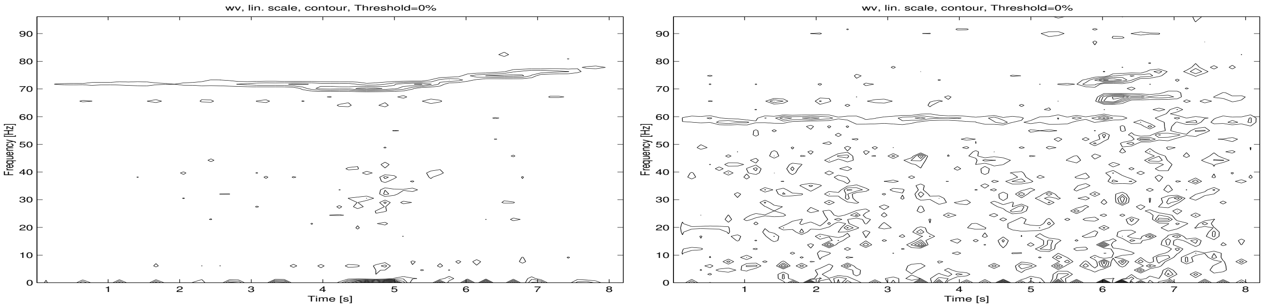

Figure 9: Tf-plots of a typical measurement (a) and component consisting of rotating machine plus wind (b)

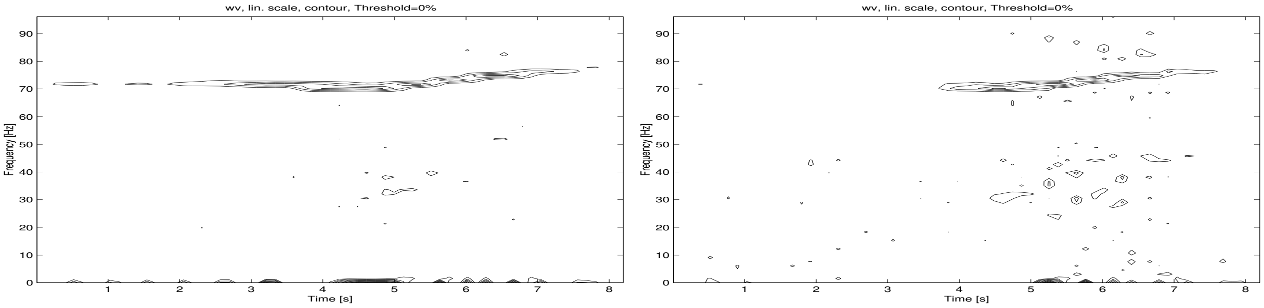

Figure 10: Tf-plots of 2 independent components in acoustic measurements: car (a) and part of car (b)

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