A convolutive Blind Source Separation based method to restore signals from electromechanical systems.

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1. Introduction & Motivation

High-speed train bearings are important parts that transmit rotary motion from the axle to the wheels. These components, under constant and recurring use, eventually become aged and fail due to defects, leading to significant costs. Thus, a number of non-invasive methods and techniques for early fault acquisition and diagnosis have emerged to aid in predictive maintenance of bearings, some approaches seek to detect bearing faults using vibration data. In these approaches, signal analysis can be applied to the data to determine the presence of a fault.

2. Blind Source Separation model

Blind Source Separation (BSS) (see [1,2,3]): the observations vector $x^0 \in R^N$ (N the number of observations), is obtained from the sources $s \in R^N$ through the mixing system up to an (unknown) additive noise $n \in R^N$:

$$x^0(t) = A \star s(t) + n(t) = x(t) + n(t), \qquad (1)$$

where $\star$ denotes the convolutive product, $x = A \star s(t)$ is the noise-free mixed vector, A is the (unknown) mixing operator and $s(t)$ is the independent component source vector.

3. Our method

Our aim: to get a good approximation of $\hat{s}$ from (1). our method we propose is decomposed into two steps:

▷ step 1: denoising the observed signal

▷ step 2: a blind source separation combined with a denoising of the estimated source.

Step 1: Denoise the observed signal

x^0, x: resp. the noisy, ideal observed stochastic signals and n a gaussian noise.
x^0, x and n_i satisfy $x^0 = x + n$.

- Reconstruct the ideal observed signal $x = (x_1, \ldots, x_N)$ from $x^0 = (x_1^0, \ldots, x_N^0)$ by means of (see [2, 3]) :

$$x_i = \arg\min \frac{1}{2}\mathbf{E}\left(\left|w_i - x_i^0\right|^2\right) + \lambda \mathbf{E}\left(\theta\left(|w'_i|\right)\right).$$

where $i \in \{1, \ldots, N\}, \lambda > 0$ is a penalization parameter, θ is a well chosen function, $w'(t)$ the first derivative of w and X is an appropriate space.

▷ The Euler-Lagrange equation:

$$w_i - \lambda\left(\frac{\theta'\left(|w_i'|\right)}{|w_i'|} w_i'\right)' = x_i^0.$$

▷ The choice of the function θ: Encourage smoothing in regions where the variation of the signal are weak ($|w'| \approx 0$). Preserve discontinuities where $|w'|$ is strong. Examples of admissible functions: $\theta(t) = t$ (Total Variation) ; other choice: $\theta(t) = \sqrt{1 + t^2}$. In the Total Variation case, a natural choice for X is $BV([0, T])^N$; the space of bounded variation function.

4. Step 2: The simultaneous BSS-denoising procedure

The purpose is to reconstruct an estimated source signal s from the partially denoised observed signal x. Our model consists in minimizing the criterion:

$$\mathcal{J}(\hat{\mathbf{s}}) = \mathcal{J}_{sep}(\hat{s}(B; x)) + \mathcal{J}_{reg}(\hat{s}(B; x)),$$

with respect to B. Here $\hat{s}(B; x) = B \star x, \mathcal{J}_{sep}$ is the separating criterion and $\mathcal{J}_{reg}$ is a regularization term:

$$\mathcal{J}_{sep}(\hat{\mathbf{s}}) = \sum_q I\left(\hat{\mathbf{s}}^q\right) \mathcal{J}_{reg}(\hat{s}) = \sum_{i=1}^{N}\left(\frac{\gamma}{2}\mathbf{E}\left(\left|\hat{s}_i - s_i^0\right|^2\right) + \mu \mathbf{E}\left(\theta\left(|\hat{s}_i'|\right)\right)\right)$$

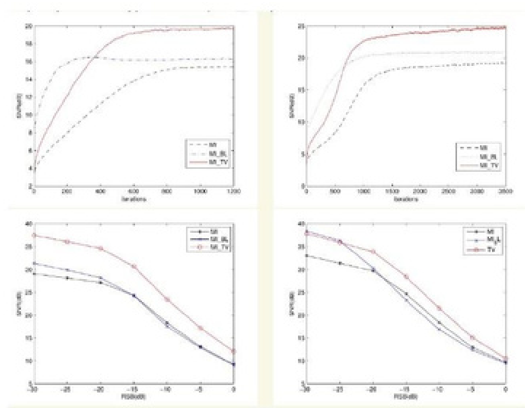
where I is the mutual information (see [1,2,3]), the reals $\gamma > 0$ and $\mu > 0$ are small regularization parameters.

5. Numerical results

Two kinds of samples: observations obtained by a convolutive mixture of two real, non-Gaussian and independent sources with zero means. The performance, in figure 1 comparison is given by:

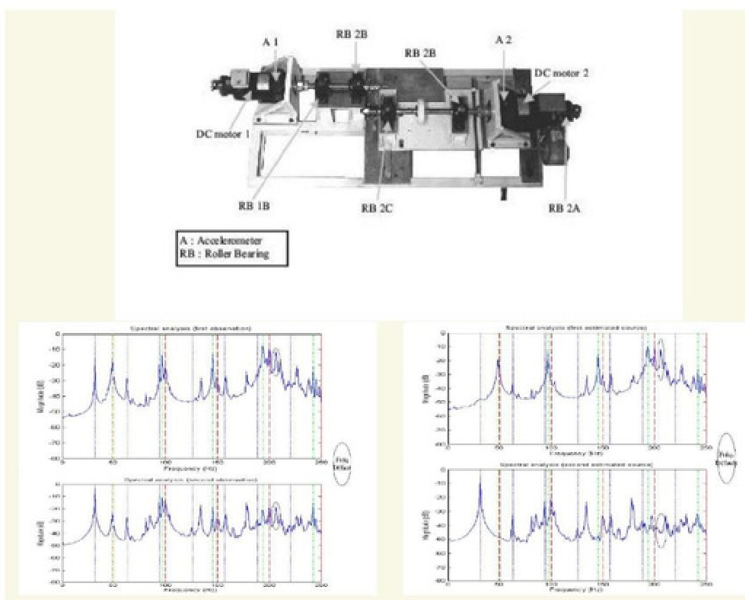
$$SNR = 10\log_{10}\left(\frac{\mathbf{E}\left(y_i^2\right)}{\mathbf{E}\left(r_i^2\right)}\right), r_i = \left(\sum_{k=1}^{L} B_k\left(\sum_{l=1}^{n-k} A_l s(n-k-l)\right)\right)\Bigg|_{s_i=0}, \; RSB = 10\log_{10}\left(\frac{P_n}{P_x}\right),$$

P_n and P_x are the noise and the noise free observed signal power. These mixtures were separated by 3 methods (MI, pre-whitening MI, our method, see([1, 2, 3])).



Application to electromechanical systems

Figure 2 illustrate that BSS can be viewed as an efficient pre-processing step.



6. References

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