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AE SOUND SOURCE LOCALIZATION USING K-SVD-BASED FEATURE EXTRACTION AND BEAMFORMING METHOD

Yong Yang[1,3], Jing Li[2] and Li Zhao[2]

[1]School of Resources and Geosciences
China University of Mining and Technology
Jiefang South Road, Xuzhou 221008, P. R. China
yongyang@cumt.edu.cn

[2]School of Information Engineering
Southeast University
No. 2, Sipailou, Nanjing 210096, P. R. China
230149053@seu.edu.cn

[3]School of Information and Electrical Engineering
Xuzhou College of Industrial Technology
No. 1, Xiangwang Road, Xuzhou 221004, P. R. China

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Abstract. *Acoustic emission (AE) source detection is an important way to evaluate incipient faults in rotating machine. This paper proposes an improved near field multiple signal classification method (IN-MUSIC) based on recognizing the accurate AE source in rub-impact. In order to decrease the computation complexity, the algorithm implements the K-SVD dictionary learning for the optimal frequency components extraction. The experiment results indicate that the improved method can accurately localize rub fault with less computation consuming than the others. Thus, it is a helpful analysis tool for on-line rub-impact fault diagnosis.*
Keywords: Rub-impact, Acoustic emission, K-SVD, Multiple signal classification

1. **Introduction.** The rotor-stator rubbing is a hazard accident in rotating machinery used in industries, and may cause dramatic damage [1]. The scratching inside rotating machine emits acoustic energy which takes lots of information. Currently, acoustic emission (AE) technique served as a kind of non-destructive fault diagnosis method keeps the rotating machinery at a healthy condition for maximum production.

By far, AE source localization is an effective way to recognize the rubbing fault and further to conclude the working condition of the machinery. The conventional time difference of arrival (TDOA) algorithm was carried out by calculating the TDOA from different sensors and then using triangulation to get the result [2-4]. Deng et al. [7] proposed generalized cross-correlation (GCC) time delay estimation of the best linear fraction Fourier transformation domain filtering and got the improved accuracy of AE rubbing source localization. However, the location error of these methods is sensitive to some parameters such as preset AE signal threshold, effective velocity, noise, dispersion and energy attenuation during propagation process of waves [8].

Beam forming method (BF), an array signal processing method, was carried out to record AE signals with different array manifold of sensors [6,11]. The advantages such as simplified sensor arrangement, unobvious channel attenuation and simultaneous localization of multiple sources can appear. Besides, in order to solve the AE essence properties problems such as fast fading and the weak energy, Deng et al. [9] investigated rubbing location algorithm of near-field BF based on minimum variance distortionless response (MVDR). The results showed that BF can be a useful way to locate the fault accurately.

Besides, the self-adaptive BF characteristic and making full use of wideband frequency information were vital to improve the location accuracy as much as possible. However, the large frequency components of the wideband AE signal and eigenvalue decomposition in every sub bands must deteriorate the computation efficiency.

Compressed sensing (CS) was a recently proposed framework that long-term AE based on structural health monitoring in the frequency domain has better sparsity [10]. In order to alleviate the computation pressure, considering AE sparsity in frequency domain, it is essential to record useful frequency representation (FR) while removing the redundant information as much as possible. Thus, we propose a new approach using pre-trained optimal dictionary for the sparsest frequency representation of the observed AE. Then the sparse frequency served as the sub narrow bands is implemented into the following near-field multiple signal classification method (N-MUSIC). In our novel approach, the dictionary is adjusted with maximum incoherent to provide the sparsest frequency points for better location accuracy and lower computation complexity.

The rest of the paper is organized as follows. In Section 2, an overview of the dictionary learning and sparse representation algorithm was introduced. In Section 3 the proposed improved near-field multiple signal classification (IN-MUSIC) model for AE source localization is presented. In Section 4 the experimental results can be shown in detail. Finally, we conclude this paper in Section 5.

2. **Dictionary Learning Processing with K-SVD.** According to the spare representation, a signal $\mathbf{Y} = \left[\mathbf{Y}_{(1)}, \ldots, \mathbf{Y}_{(M)}\right] \in R^{N\times M}$, a dictionary $\mathbf{D} = \left[\mathbf{d}_{(1)} \cdots \mathbf{d}_{(L)}\right] \in R^{D\times L}$ consisting of L unit-norm atoms, and the K-sparse coding vector $\mathbf{X} = \left[\mathbf{X}_{(1)}, \ldots, \mathbf{X}_{(M)}\right] \in R^{L\times M}$, $K \ll L$, the signal can be described by a sparse linear combination of atoms as $\mathbf{Y} = \mathbf{DX}$. Hence, the sparse representation problem can be presented that the approximation reconstruction error $\|\mathbf{Y} - \mathbf{DX}\|_2$ is sufficiently small and then the useful AE signal can be well approximated by few atoms of a suitably trained dictionary [5].

Dictionary learning using the constructed dictionary can better adaptively achieve sparse signal representations. Therefore, the dictionary learning problem subject to sparsity constraint on $\mathbf{X}$ and the unit norm constraint on $\mathbf{D}$ can be given as follows:

$$\arg\min_{\mathbf{D},\mathbf{X}} \|\mathbf{Y} - \mathbf{DX}\|_F^2 \text{ s.t. } \left\|\mathbf{X}_{(i)}\right\|_0 < K,\ 1 \le i \le L \tag{1}$$

In Equation (1), $\|\cdot\|_F$ is the Frobenius norm and $\mathbf{X}_{(i)}$ is the column of $\mathbf{X}$. Since the joint optimization of D and X is non-convex, the optimal solution is difficult to calculate. K-SVD algorithm is an iterative solver by alternating between optimizing the coding and the dictionary [12]. The two steps of K-SVD are as follows.

Coding update: The orthogonal matching pursuit (OMP) algorithm is used for sparse coding for its predefining the sparsity and its good compromise between complexity and performance. For each column $\mathbf{X}_{(i)}$ with some small value σ, it can be calculated by:

$$\arg\min \left\|\mathbf{X}_{(i)}\right\|_0 \text{ s.t. } \left\|\mathbf{Y}_{(i)} - \mathbf{DX}_{(i)}\right\|_2 \le \sigma,\ 1 \le i \le L \tag{2}$$

Dictionary update: For each atom $\mathbf{d}_{(l)}$ is isolated by rewriting the term $\|\mathbf{Y} - \mathbf{DX}\|_F^2$:

$$\begin{aligned} \|\mathbf{Y} - \mathbf{DX}\|_F^2 &= \left\|\left(\mathbf{Y} - \sum_{j=1}^{L} \mathbf{d}_j \mathbf{x}_j^T\right)\right\|_F^2 = \left\|\left(\mathbf{Y} - \sum_{j\neq k} \mathbf{d}_j \mathbf{x}_j^T\right) - \mathbf{d}_k \mathbf{x}_k^T\right\|_F^2 \\ &= \left\|\mathbf{E}_k - \mathbf{d}_k \mathbf{x}_k^T\right\|_F^2 \end{aligned} \tag{3}$$

where $\mathbf{x}_j^T$ stands for the jth row of $\mathbf{X}$. The dictionary can be updated by $\min\left\|\mathbf{E}_k - \mathbf{d}_k \mathbf{x}_k^T\right\|_F^2$, where the singular value decomposition (SVD) method is involved to compute the update $\mathbf{d}_{(i)}$ as the first column of $\mathbf{U}$ and $\mathbf{X}_{(i)}$ as $\mathbf{\Sigma}_{1,1}$ times the first row of $\mathbf{V}^T$.

$$\mathbf{E}_k = \mathbf{U}\Sigma\mathbf{V}^T \tag{4}$$

3. Proposed Method for Sound Source Localization.

3.1. **Experiment.** The test table of the rotary machine rubbing fault localization was carried out in Figure 1. Four AE sensors were arranged in a line at the end of the arch case made by 10mm thick, steel plate. The reference coordinate was placed in the left of the linear sensor array and the aperture array was 50mm. In the test, the rubbing screw rubbed the rotor at preset position, and the AE acquisition system made by PAC Corporation, recorded test data at the sampling frequency 1MHz, duration time 5kms and with 60dB pre-amplifier to obtain optimal AE records.

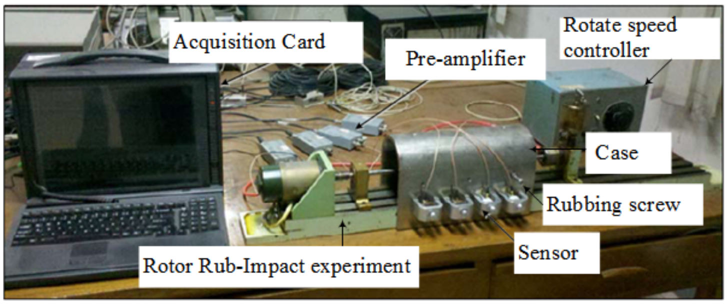

FIGURE 1. Experimental setup of the rotary machine

3.2. **K-SVD-based feature extraction method.** The wideband AE signal received at the sensor array should be decomposed into N narrow sub-bands according to frequency components using N sample points discrete Fourier transform (DFT). Considering the conjugate symmetry, the expression of the nth frequency components is described by:

$$\mathbf{S}(f_k) = \sum_{n=0}^{N-1} s(n) e^{-j\frac{2\pi f_k n}{N}}$$
$$f_k = (n-1)/N \text{ where } n = 1, 2, \ldots, N/2 \tag{5}$$

The sparse AE coding in frequency domain $\mathbf{S}(f_k)$ can be gotten by using the over complete basis FFT. In our K-SVD-based feature extraction method in Algorithm 1, the atoms in the dictionary can be updated for the major components representations of AE signal in frequency domain. Thus, the irrelevant background noise and some interferences can be filtered away and the following localization computation pressure can be obviously reduced by using less frequency bins.

Algorithm 1: K-SVD

Input: Training signal $\mathbf{Y} \in R^{N\times M}$, initial dictionary $\mathbf{D}_0 \in R^{\mathbf{D}\times L}$, target co-rank N-K and number of iterations I

Output: Dictionary D and signal set $\mathbf{X}$ minimizing

1. Initialization: Set $\mathbf{D} := \mathbf{D}_0$
2. Sparse coding stage: use OMP algorithm to compute the representation vector $\mathbf{x}_{(i)}$ for each signal $\mathbf{Y}_{(i)}$ by approximating the solution of $\arg\min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2$ s.t. $\left\|\mathbf{X}_{(i)}\right\|_0 < K,\ 1 \le i \le L$
3. Codebook update stage: define the group of examples that use this atom, $\boldsymbol{\omega}_k = \left\{i | 1 \le i \le K, x_T^k(i) \ne 0\right\}$
4. Compute the overall representation error matrix, $\mathbf{E}_k^R$, by $\min_{\mathbf{d}_k, \mathbf{x}_R^k} \left\|\mathbf{E}_k^R - \mathbf{d}_k \mathbf{x}_R^k\right\|_F^2$
5. Apply SVD decomposition $\mathbf{E}_k^R = \mathbf{U}\Delta\mathbf{V}^T$
6. Update dictionary column $\mathbf{d}_k$ and the coefficient vector $\mathbf{x}_R^k$

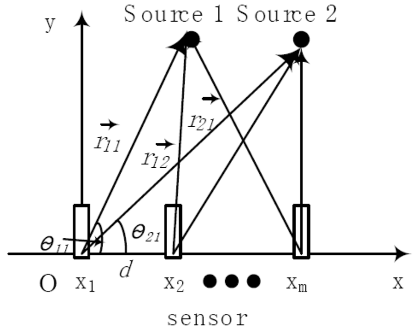

FIGURE 2. Illustration of nearfield localization model

3.3. **Localization via frequency sparsity.** The definition of near field source as shown in Figure 2, a linear sensor array with m elements is arranged on the structure. Source 1 and source 2 are preset AE sources respectively. The output of these incident spherical waves can be illustrated by Equation (6), where p is the number of the sources $p < m$, $x_m(t)$ is the records from the mth sensor, $\mathbf{a}(\mathbf{r}_p, \boldsymbol{\theta}_p)$ is the direction and distance vector from reference sensors to AE source; furthermore, $\mathbf{r}_{p1}$ and $\boldsymbol{\theta}_{p1}$ are the distance and the angle of arrival from the pth AE source to the referenced sensor separately, and $\mathbf{r}_{pm}$ is the distance from the pth AE source to the mth sensor, and f is the signal frequency.

$$\begin{aligned} &\tau_m = \frac{\sqrt{\mathbf{r}_{p1}^2 + (m-1)^2 d^2 - 2\mathbf{r_1}(m-1)d\cos\boldsymbol{\theta}_{p1}} - \mathbf{r}_{p1}}{c} \\ &\mathbf{a}(\mathbf{r}_p, \boldsymbol{\theta}_p) = \exp[j2\pi f \tau_m] \\ &\mathbf{x_m}(t) = \mathbf{a}(\mathbf{r}_p, \boldsymbol{\theta}_p)\mathbf{s_m}(t) + \mathbf{e_m}(t) \end{aligned} \tag{6}$$

Then the M group received wideband signal in the time domain are taken $\mathrm{N_0}$-point DFT at discrete frequency points f_j $(j = 1, 2, \ldots, J)$ to form several sub-bands, and the each sub-band output $\mathbf{X}(f_j)$ is as follows:

$$\mathbf{X}(f_j) = \mathbf{A}(\mathbf{r}, \boldsymbol{\theta}, f_j)\mathbf{S}(f_j) + \mathbf{N}(f_j) \tag{7}$$

where:

$$\begin{aligned} &\mathbf{X}(f_j) = [x_1(f_j), x_2(f_j), \ldots, x_m(f_j)]^T \\ &\mathbf{A}(\mathbf{r}, \boldsymbol{\theta}, f_j) = [a_1(\mathbf{r}_1, \boldsymbol{\theta}_1, f_j), a_2(\mathbf{r}_2, \boldsymbol{\theta}_2, f_j), \ldots, a_m(\mathbf{r}_p, \boldsymbol{\theta}_p, f_j)]^T \\ &\mathbf{S}(f_j) = [s_1(f_j), s_2(f_j), \ldots, s_p(f_j)]^T \\ &\mathbf{N}(f_j) = [n_1(f_j), n_2(f_j), \ldots, n_m(f_j)]^T \end{aligned}$$

Here, $\mathbf{X}(f_j)$, $\mathbf{S}(f_j)$ and $\mathbf{N}(f_j)$ are the DFT transformations of the observed signal, denoising signal and noise vectors, and $\mathbf{A}(\mathbf{r}, \boldsymbol{\theta}, f_j)$ is $m \times p$ matrix location vectors with p full-rank. Then the covariance matirix under this frequency is given by:

$$\mathbf{R}(f_j) = \mathbf{X}(f_j)\mathbf{X^H}(f_j) \tag{8}$$

As shown in Figure 3(a), the one AE event recorded the entire rubbing fault in time domain with 5120 points. The record is mapped into 8192-points FFT in Figure 3(b). The energy spread over all of the frequency domain. In the experiment, the parameter are set as: 853 items training data, 100 items testing data, DCT dictionary. As the result the 1000-sparsity, the obviously emerged major energy stands at the non-zero frequency bins in Figure 3(c). As the smaller K is, the less quantity of non-zero frequency bins can be and the stronger energy components can be kept in Figure 3(d).

Near-field multiple signal classification algorithm (N-MUSIC) in Equation (9) divides the covariance matrix $\mathbf{R_{ss}}(f_j)$ into signal subspace and noise subspace using eigen decomposition approach, where the maximum eigenvector $\mathbf{U_{SX}}$ and eigenvalue $\mathbf{\Sigma_{SX}}$ correspond

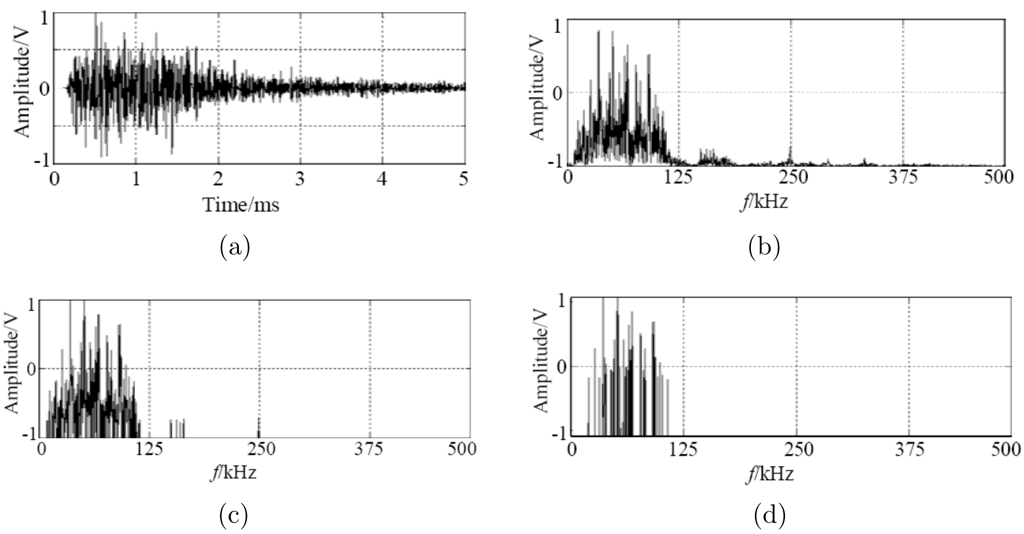

Figure 3. The observed AE signal at reference sensor: (a) the signal in time domain; (b) the signal in frequency domain; (c) the 1000-sparsity in frequency domain; (d) the 200-sparsity in frequency domain

to the signal subspace and the $\mathbf{U_{SN}}$, and $\mathbf{\Sigma_{SX}}$ mean the maximum eigenvector and eigenvalue of noise subspace [11].

$$\mathbf{R_{ss}}(f_j) = \mathbf{U_{SX}}(f_j)\mathbf{\Sigma_{SX}}(f_j)\mathbf{U^H_{SX}}(f_j) + \mathbf{U_{SN}}(f_j)\mathbf{\Sigma_{SN}}(f_j)\mathbf{U^H_{SN}}(f_j) \tag{9}$$

Based on the condition, the signal subspace orthogonal with noise subspace. Then the multiple signal classification spectrum is presented by:

$$\mathbf{P}(\mathbf{r}, \boldsymbol{\theta}, f_j) = \frac{1}{\mathbf{a^H}(\mathbf{r}, \boldsymbol{\theta}, f_j)\mathbf{R_{SN}}(f_j)\mathbf{a}(\mathbf{r}, \boldsymbol{\theta}, f_j)} \tag{10}$$

As the parameters $\boldsymbol{\theta}$ and $\mathbf{r}$ updated constantly, the spectrum peak is the result to locate AE source. However, the localization results can hardly be unique in accordance with different frequency components. It is difficult to find the exact solutions from these scatters. The K-means classifier can be applied to divide these scatters and find the final solution of the AE source localization.

4. **Simulations and Evaluations.** Figure 4 shows the localization results based on the N-MUSIC, IN-MUSIC, TDOA, and DTB methods. Three events at each preset source location are required to provide an average result and allow erroneous data to be away.

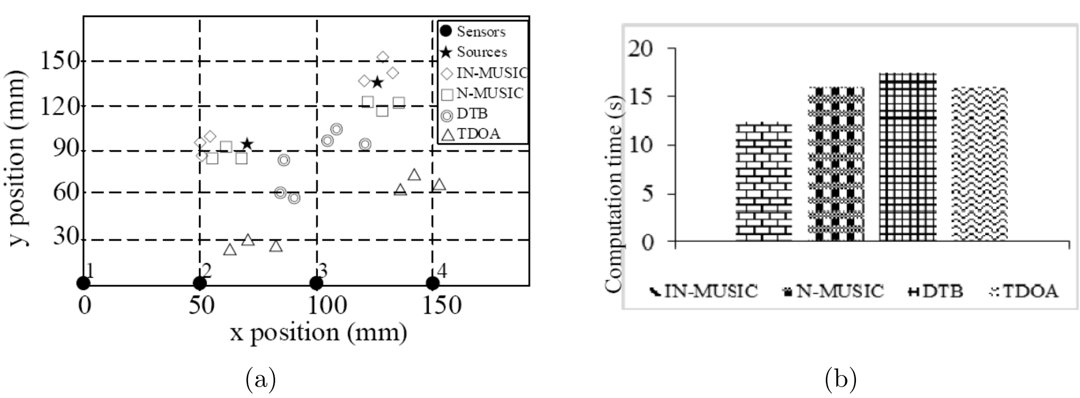

Figure 4. Comparison with the IN-MUSIC, N-MUSIC, DTOA, and DTB methods: (a) localization results (mm); (b) computation time (s)

From the results in Figure 4(a), the IN-MUSIC and N-MUSIC methods can approximate to the real AE source as much accurately as possible, since the covariance matrix eigen decomposition at each frequency bins makes the best use of sub-bands information and some noise effects are filtered away. Besides, the computational complexity of IN-MUSIC is superior to N-MUSIC since the K-SVD reduces the quantity of non-zero frequency bins so as to the eigen decomposition times. Therefore, considering these factors, the proposed IN-MUSIC method is a useful approach to monitor the sole rubbing fault source in rotary machine.

5. **Conclusions.** This paper proposes a novel nearfield MUSIC algorithm into detecting AE source in rotor rubbing. The superiorities of this algorithm are the optimal sparse frequency components extraction using K-SVD dictionary learning method for the following N-MUSIC algorithm for improved localization accuracy and computation efficiency. The experiment results show that IN-MUSIC algorithm can be considered as the best candidate for AE source localization methodology to be utilized for the fatigue location diagnosis of rotor rubbing in rotary machine. Further work aims to complete the workability of this method for detection of multi-sources in rubbing and impacting.

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REFERENCES

[1] P. S. Keogh, Contact dynamic phenomena in rotating machines: Active/passive considerations, *Mech. Syst. Signal Processing*, vol.29, no.5, pp.19-33, 2012.

[2] R. K. Miller and P. Mc Intire, *NDT Handbook, Vol.5, Acoustic Emission Testing*, ASNT, 1987.

[3] P. Kundu, N. K. Kishore and A. K. Sinha, A non-iterative partial discharge source location method for transformers employing acoustic emission techniques, *Applied Acoustics*, vol.70, no.11, pp.1378-1383, 2009.

[4] M. G. Baxter, R. Pullin and K. M. Holford, Delta T source location for acoustic emission, *Mechanical Systems and Signal Processing*, vol.21, no.3, pp.1512-1520, 2007.

[5] M. Samira, S. M. Ahadi and S. Seyedin, Modified coherence-based dictionary learning method for speech enhancement, *IET Signal Processing*, vol.9, no.7, pp.537-545, 2015.

[6] J. Li, A. Deng, D. Liu, R. Zhang and L. Zhao, Near-field multiple signal classification algorithm for acoustic emission source localization in rolling element rub-impact fault diagnostics, *ICIC Express Letters*, vol.10, no.3, pp.663-668, 2016.

[7] A. Deng, Y. Bao and L. Zhao, Research on time delay estimation algorithm based on generalized cross correlation in acoustic emission source location, *Proc. of the CSEE*, pp.86-92, 2009.

[8] J. L. Rose, *Ultrasonic Waves in Solid Media*, Cambridge University Press, London, 2004.

[9] A. Deng, H. Tong, J. Tang et al., Study on location algorithms of beamforming based on MVDR, *Applied Mathematics & Information Sciences*, vol.7, no.6, pp.2455-2466, 2013.

[10] M. Genussov and I. Cohen, Multiple fundamental frequency estimation based on sparse representations in a structured dictionary, *Digital Signal Processing*, vol.23, no.1, pp.390-400, 2013.

[11] J. L. F. Chacon, V. Kappatos and W. Balachandran, A novel approach for incipient defect detection in rolling bearings using acoustic emission technique, *Applied Acoustics*, vol.89, pp.88-100, 2015.

[12] Z. Tang, Z. Yang and S. Ding, A new dictionary learning method for sparse representation, *ICIC Express Letters*, vol.5, no.5, pp.1535-1540, 2011.