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Mechanical failure acoustic diagnosis using frequency domain semi-blind extraction method

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ABSTRACT

It's usually very difficult to extract fault features from the acoustic signals directly, since the complexity of the mechanical structure and the serious background interference in industry testing site. In order to deal with these kinds of monitoring problems, a mechanical failure acoustic diagnosis method based on reference signal frequency domain semi-blind extraction is proposed. In this method, dynamic particle swarm algorithm is used to construct improved multi-scale morphological filters which applicable to mechanical failure in order to weaken the background noises; thus reference signal unit semi-blind extraction algorithm is applied to do complex components blind separation band by band, coupled improved KL-distance of complex independent components are employed as distance measure to resolve the permutation; finally the estimated signal could be extracted and analyzed by envelope spectrum method. Comparing to the time-domain blind deconvolution algorithm based on fuzzy clustering, it has several advantages such as more effectively and more accurately. Results from acoustics rolling bearing fault diagnosis experiment validate the feasibility and effectiveness of proposed method.

KEYWORDS

Frequency-domain blind deconvolution; Mechanical acoustical diagnosis; Improved KL-distance, Reference signal, semi-blind extraction.

INTRODUCTION

The vibration signals generated by mechanical equipment's failures will contain some significant impact components. Meanwhile, acoustic signals' characteristics which related to these vibration signals will also be changed [1]. The crucial issues of Machine fault diagnosis largely dependent on how to extract adequate and effective features from the numerous and complex mechanical status signals [2]. Acoustical fault diagnosis method has several advantages comparing with the traditional vibration monitoring method, such as non-destruction, non-contact and simple using etc. [3]. However, it's usually very difficult to extract fault features from the acoustic signals directly, since the complexity of the mechanical structure and the serious background interference in industry testing site. In order to identify the cause of the fault by symptom of failure, these interferences or noise should be suppressed or eliminated before further processing [4].

In recent years, the blind signal processing (BSP) which could recover or estimate source signals from mixed-signals without any prior knowledge provides an effective way to solve mechanical sound features extraction issues. Still, there're many traditional blind separation algorithm which couldn't carry out mechanical fault feature identification and extraction effectively [5]. While the blind deconvolution algorithm is more suitable for practical industrial sound field environment [6].

This paper is organized as follows. The problem statement including the frequency blind deconvolution issue is introduced in Section 2. Section 3 presents the fault acoustic diagnosis method based on frequency domain semi-blind extraction. In Section 4, experimental results from rolling bearing acoustical signals are presented and analyzed. The final section gives the conclusion which obtained from the above results.

PROBLEM STATEMENT

The basic steps of frequency-domain blind deconvolution could be described as follows: First of all, convert the time-domain observed signals into frequency-domain through windowed STFT, in this case, the time-domain convolution is transformed into instantaneous mixture on each neighbor frequency band, so as to bring a complex blind separation algorithm to estimate the complex source components. Then, reorder the complex estimated components in each sub-band to resolve the permutation. After the permutation problems are resolved, the time-domain signals are reconstructed by using windowed inverse STFT for further analysis [2].

Mechanical system will generate a variety of signals in the industrial site, which are mixed together with the background noise. Therefore, the application of mechanical failure frequency-domain blind deconvolution in complex sound field will face many practical problems [7]:

1) Mechanical sound field is more complex and would be disturbed by multiple sources, failure characteristic could easily be drowned by strong Gaussian noise, other complex periodic signal and non-stationary signals.

2) The microphones' mounting position are often far from the failure sources, acoustic signal may have attenuation because of the long convolution during transmission, which will increases the difficulty of algorithm solving.

3) The inherent problems like cycle-part convolution error and permutation problem will both affect the separation performance when applying frequency-domain blind deconvolution algorithm to do fault feature extraction.

4) Traditional frequency-domain blind signal processing algorithms are often unable be directly applied to mechanical failure signals' extraction.

FREQUENCY DOMAIN SEMI BLIND EXTRACTION METHOD FOR ROLLING BEARING FAULT ACOUSTIC DIAGNOSIS

To address the above problems, the original frequency-domain blind deconvolution algorithm need to be improved, so as to weaken the background noise and highlight the characteristic frequency range when applying it into practical mechanical acoustic diagnosis.

Improved multi-scale morphological filter

In recent years, the morphological filter which is widely used in mechanical signal detail features extraction and background noise suppression. Its filter structure is based on difference filter or morphological open-closed (OC) and closed-open (CO) average combination, and the structural elements are often single structural elements [8]. However, there're often more than only one interference noise in practical industrial acoustic field, and the noise in signal is usually random. Different structural elements multi-scale morphological filters need to be built in order to avoid serious statistical bias of filter output [9].

For problems of particle effective optimization, dynamic particle swarm algorithm is used to make an extreme optimization of maximum and minimum of neighbor peaks in observed signals, hence the length of structural elements may be determined [10]. Furthermore, the height range may be determined through maximum and minimum of signal peaks. Finally, the corresponding structural element sizes are substituted into the semi-circular and triangular structural equation to calculate their own sets of structural elements [11].

The algorithm steps of dynamic particle swarm optimization are as follows:

1) Firstly, initialize the position h and velocity v of the particle swarm, and then initialize the particle position of sensitive particle swarm;

2) Secondly, calculate the fitness value under the current environment, and then update the velocity and position of particle according to current individual and population optimal particle;

$$fitness(i) = positionx(i) + positiony(i) \quad (1)$$

3) Finally, calculated the fitness value of sensitive particle based on the current environment, if the value changes exceeds the threshold, the population re-initialized in proportion, if not, end the calculation or do re-fitness calculation according to termination conditions is met or not.

Algorithm steps of improved multi-scale morphological filtering algorithm are as follows:

1) Initialize multi-scale structure element λ_g;

2) Calculate the local maxima & minima value of observed signal $x(t)$, determine the height H_L and length K_L of the set of structural elements.

3) Substitute the H_L and K_L into the equation of the triangular and semi-structural elements, in order to construct the structural elements set g_1 and g_2.

4) Substitute the g_1 and g_2 into the following equation, to get the combination filter set of $y(n)$.

$$y1(n) = (f \oplus g_1 \Theta g_1 \Theta g_2)(n)$$
$$y2(n) = (f \oplus g_1 \Theta g_1 \Theta g_2 \oplus g_2)(n) \quad (2)$$
$$y(n) = [y1(n) + y2(n)]/2$$

5) Optimize the filter set using dynamic particle swarm optimization algorithm, use $y(n)$ to do filter processing for $x(t)$, until get the final de-nosing signal. The specific process is shown in Figure 1.

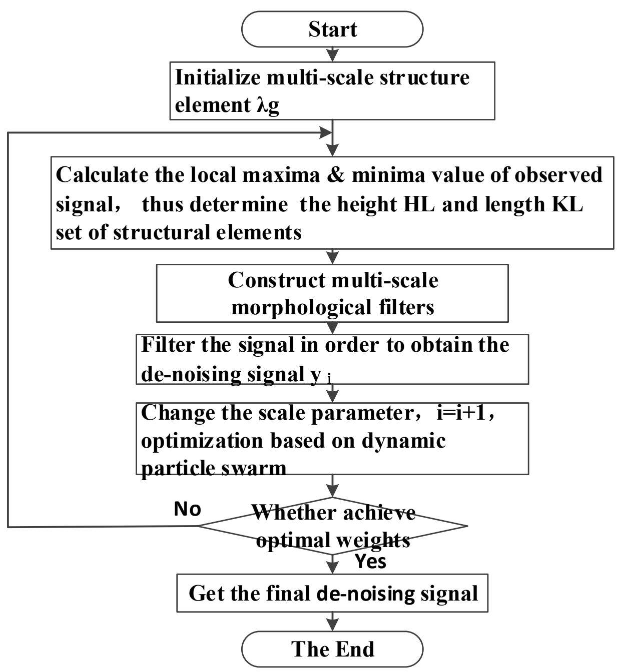


Figure 1. The flow of improved multi-scale morphological filtering algorithm

Reference signal constrained semi-blind extraction algorithm

Construct a reference signal based on the structure of key components in machinery and equipment, in order to reduce the complexity of the algorithm [12]. And as a constraint, to execute similarity measurement between measurement signal and reference signal to extract a limited number of estimated signals, this progress is so called semi-blind extraction. Unit reference signal constraints semi-blind extraction is described as follows:

$$J(y) \approx \rho\left[E\{G(y)\} - E\{G(r)\}\right]^2$$
$$g(w) = \varepsilon(y,r) - \xi \le 0 \quad (3)$$

Constraint conditions: $g(w) \le 0, h(w) = E\{y^2\} - 1 = 0$

Where $J(y)$ is Negative entropy of objective function; $\varepsilon(y,r)$ represent the similarity measurement between observed signal and reference signal; ξ is the discrimination threshold between estimated signal and other signals, its selection is gradual adaptation process, which could guarantee the solvability constraints objective function and avoid falling into local optimum simultaneously.

$$L(w,\mu) = J(y) - \frac{1}{2\gamma}\left[\max^2\left\{\mu + rg(w), 0\right\} - \mu^2\right] - \lambda h(w) - \frac{1}{2}\gamma\left\|h(w)\right\|^2 \quad (4)$$

Where μ and λ are Lagrange multipliers, and γ is scale penalty parameter, Newton iterative algorithm could be obtained as follows:

$$\begin{aligned} w_{k+1} &= w_k - \eta R_{xx}^{-1} L_{wk}^{''} \big/ \delta(w_k) \\ L_{wk}^{'} &= \rho E\left\{xG_y^{'}(y)\right\} - 0.5\mu E\left\{xg_y^{''}(w_k)\right\} - \lambda E\left\{xy\right\} \\ \delta(w_k) &= \rho E\left\{xG_{y^2}^{''}(y)\right\} - 0.5\mu E\left\{xg_{y^2}^{''}(w_k)\right\} - \lambda \end{aligned} \quad (5)$$

Where η is the learning rate, R_{xx} is the covariance matrix of mixed signals, $G_y^{'}$, $G_{y^2}^{''}$ and $g_y^{''}(w_k)$, $g_{y^2}^{''}(w_k)$ represent the first derivative and second derivative of G_y and $g_y(w_k)$ respectively, μ and λ are obtained by equation (5):

$$\mu_{k+1} = \max\left\{0, \mu_k + \gamma g(w_k)\right\}$$
$$\lambda_{k+1} = \lambda_k + \lambda h(w)$$

When the signal run after Whitening and central processing, $R_{\bar{xx}}$ =1, and the equation (4) could be written as the following form:

$$w_{k+1} = w_k - \eta L_{wk}^{'} \big/ \delta(w_k) \quad (6)$$

Where:

$$p_j(\omega) = \left[p_j(\omega,1), ..., p_j(\omega,M)\right], j = 1, ..., J, l = 1, ..., J;$$

$$p_j(\omega,m) = \frac{p_{j,fre}(\omega,m) \bullet \left|\tilde{Y}_j(\omega,m)\right|^2}{\sum_{r=1}^{M}\left|\tilde{Y}_j(\omega,r)\right|^2}$$

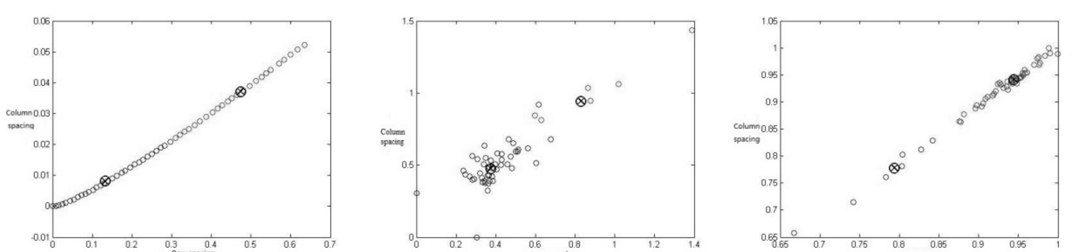
The solution of permutation problem based on improved KL-distance

Distance measurement has been widely applied to measure the degree of similarity between two signals, the greater the distance is, the smaller the similarity of two signals are, or vice versa. The basic principle of distance mutual parameter method is to adjust the output of each frequency band to the same source [13].

Improved KL distance can be used to describe the distance between the probability density related to two complex-valued signals in adjacent frequency bands.

$$KL(p_j(\omega), p_i(\omega+1)) = \sum_{m=1}^{M} p_j(\omega,m) \bullet \log\frac{p_j(\omega,m)}{p_i(\omega+1,m)} \quad (7)$$

In order to verify the advantage of improve KL distance in complex components similarity computation, a simulation was carried out: Improved KL-distance, Kurtosis index and Cosine measure are used respectively to do Similarity clustering calculation for 18 groups of complex components. As can be seen from the cluster scatter diagram Figure 2, the distance cluster scatter linear degree calculated by improved KL-distance is better than the other two indexes.



(a) Clustering by improve KL distance (b) Clustering by kurtosis index (c) Clustering by cosine measure
Figure 2. Comparison of similarity clustering effects

The main steps of the proposed method

Finally, the main steps of the proposed method are summarized as follows:

1) Initialization components structural parameters, calculate the characteristic frequencies based on the structural parameters, construct a reference signal $r(t)$;

2) Use the improved multi-scale morphological filters to do noise suppression for $\boldsymbol{x}(t)$, and then obtain the filtered signals $\tilde{\boldsymbol{x}}(t)$;

3) Convert the observed signals $\tilde{\boldsymbol{x}}(t)$ and $r(t)$ into frequency-domain through windowed STFT, to get their expression patterns in frequency domain $X(\omega,t)$ and $R(\omega,t)$;

4) Apply unit reference signal constraints semi-blind extraction algorithm to do complex components blind separation band by band, coupled improved KL-distance of complex independent components are employed as distance measure to resolve the permutation. After that, the complex value estimated signal $Y(\omega,t)$ which most similar to the reference signal $R(\omega,t)$ will be achieved.

5) Convert the estimated signal back to time domain through windowed ISTFT.

6) Finally, the estimated signal could be analyzed by envelope spectrum method.

EXPERIMENTAL VALIDATION

In this section, to further investigate the effectiveness of the presented algorithm for bearing fault diagnosis, a rotating machine fault test rig is set up. This experiment use a fault rolling bearing (Type NU205) as a diagnostic target, the bearing outer ring is fixed, and the inner ring rotates with the shaft, and its failure type and location are both unknown. Its relevant physical parameters are shown in Table 1.

TABLE1 The parameters of rolling bearing

Model	Pitch circle diameter D (mm)	Ball diameter d (mm)	Ball number Z	Contact angle ($^{\circ}$)
NU 205	39	7.5	12	0

Data acquisition system is made up of MPA416 1/4 TEDS microphones, NI CRIO-9082 control chassis, and NI-9234 sound acquisition card. The Acquisition software which is programmed with NI-LabVIEW, and the Analysis algorithm is programmed with Matlab. In this experiment, we used Envelope spectrum based on Hilbert transform to do bearing fault detection, when bearing defections occur, some characteristic frequencies can be obtained by performing spectrum analysis on the envelope signal [15].

Operating conditions and bearing fault characteristic frequency are shown in Table 2:

TABLE 2 The operation condition and bearing failure frequencies in experiment

Rpm	Rotation frequency f_r	Outer race characteristic frequency f_{outer}	inner race Characteristic frequency f_{inner}
800r/min	13.33Hz	64.61Hz	95.38Hz

The sampling frequency is set to 8192Hz because of the fault characteristic frequencies are concentrated in low frequency band.

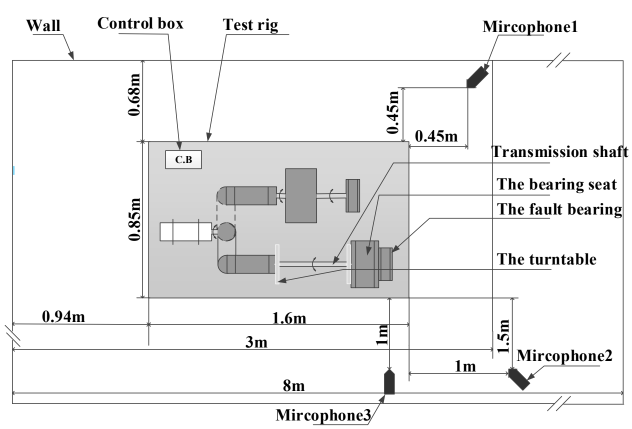
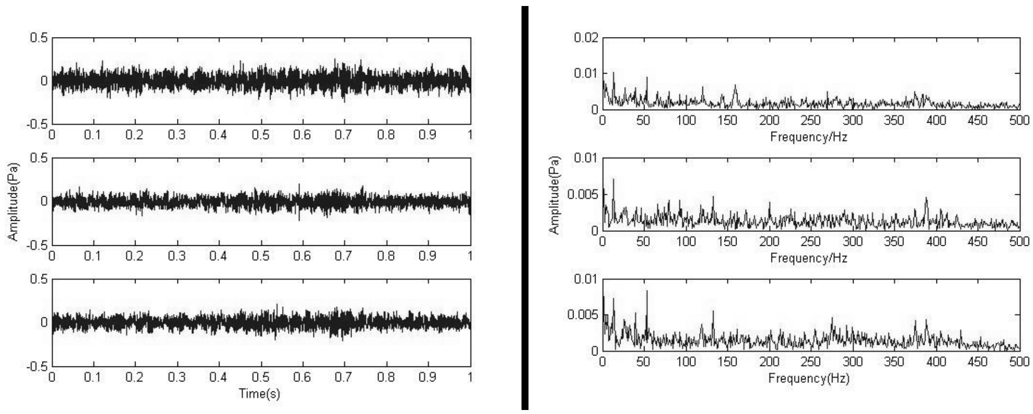


Figure 3. The position chart of test-rig and microphones

The microphones are one meter from the ground, and all point to the bearing set. Straight-line distance from the three microphones to test bed edges are 0.64m, 1.81m and 1.5m respectively. Microphone1 and microphone2 are made 90° to each other. The "Close measurement" principles and sound-absorbing panels are not used in order to close to the real industrial environment. The positional relationship between the test stand and microphones is shown in Figure 3.

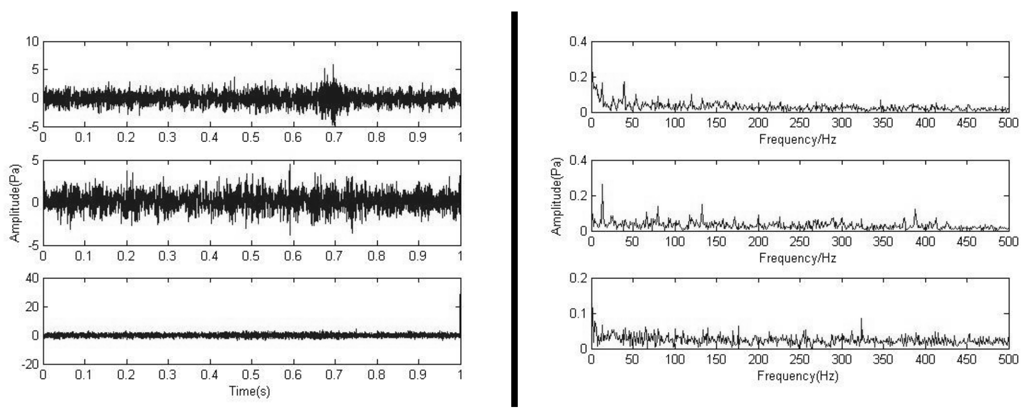
Turn on the drive motor, until the motor speed is stabilized at 800 r/min, then start acoustic signal acquisition. After the acquisition progress is completed, one second data (8192 points) from the original data in case of steady-state operation is picked up for further analysis. Figure 4. presents the time-domain waveform and amplitude spectrum of the observed signals, signals in 3 channels are mixed with each other, only motor rotation frequency spectrum (13Hz) is barely visible, while failure impact signal has been completely submerged by interference noise.



(a) Time domain waveform **(b) Amplitude spectrum**

Figure 4. Measurement signals

To compare with the proposed algorithm, the time-domain blind deconvolution algorithm based on fuzzy clustering is used to process the observed signals, the step length is set to 2 and the number of clusters is set to 3 [14]. The extraction result is shown in Figure 5., 3 estimated signals are obtained, but still no significant impact component could be recognized.



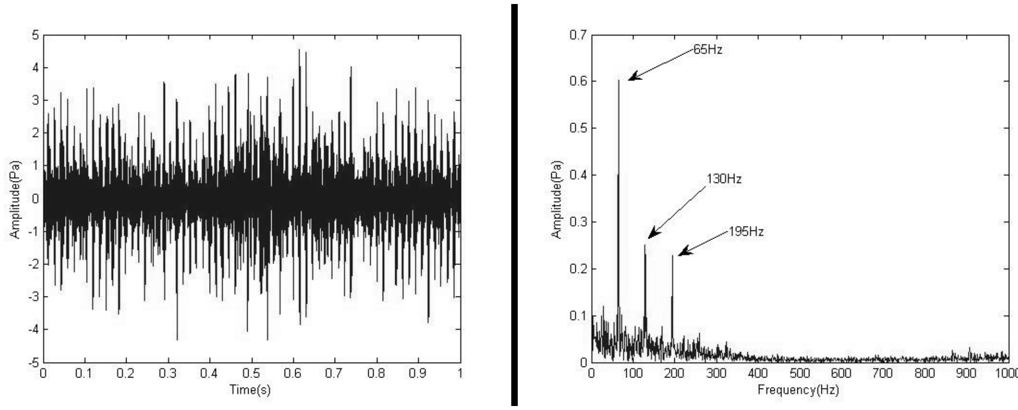
(a) Time domain waveform **(b) Envelope spectrum**

Figure 5. Signals separated by the time-domain blind deconvolution algorithm based on FCM

Then, we use the proposed reference signal frequency domain semi-blind extraction method to process the observed signals. The STFT frame length is set to 512, add Hanning windows, windows length is 512, windows mobile length is 64; triangle and semi-circular structure elements are used to build multi scale morphological filter for background noise reduction.

Figure 6. shows the extraction algorithm result, three spectrum lines (65Hz, 130Hz, 195Hz, resolution = 1Hz) could be obviously found from the envelope spectrum data of first separated signal in Figure 6. (b). They're roughly consistent with outer race features (64.7Hz and its harmonic frequencies) by compare with data in Table 2.

Thus, the fault location could be determined, crack is found in bearing outer race after dismounted the bearing (seen in Figure 7.), consistent with the acoustic diagnosis result. The analysis results of the experimental data verify the validity and effectiveness of the proposed method in extracting the fault diagnostic information blindly from the strong background noise.



(a) Time domain waveform **(b) Envelope spectrum**

Figure 6. Signals separated by reference signal frequency domain semi-blind extraction method

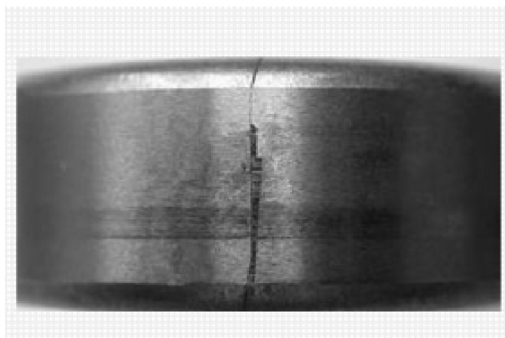


Figure 7. Schematic diagram of bearing outer crack fault

CONCLUSIONS

In order to deal with the problems caused by complex machinery parts and serious background noises, a failure acoustic diagnosis method based on reference signal frequency domain semi-blind extraction is proposed. In this method, dynamic particle swarm algorithm is used to construct improved multi-scale morphological filters which applicable to mechanical failure in order to weaken the background noises; thus reference signal unit semi-blind extraction algorithm is applied to do complex components blind separation band by band, coupled improved KL-distance of complex independent components are employed as distance measure to resolve the permutation; finally the characteristic signals are extracted and separated. Results from acoustics rolling bearing fault diagnosis experiment validate the feasibility and effectiveness of proposed method.

Prerequisites of vehicle break acoustic blind signal processing are consistent with prerequisites of common mechanical sound field blind signal processing. The acoustic source identification both in industrial field and road test condition are all facing problems like multi-path effects of signal propagation and serious environment noise interference. Therefore, the vehicle break acoustic signal blind extraction issues are worthy to be studied further based on the research results of mechanical acoustic signal blind signal processing.

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