Crack Detection of Propeller Shaft on board Marine Ship using Microphone Array

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Abstract. Vibration due to rotation of a shaft of a ship propeller may cause crack due to lack of proper maintenance. It is considered to be hazardous area to conduct a direct measurement on rotating shaft using accelerometer. In this paper, acoustic emission using linear microphone array is proposed to collect acoustical data emitted from the rotation of the shaft. In a semi-anechoic chamber, the proposed technique using single microphone may have detected a crack in propeller shaft by observing the peak of the main spectrum. In engine room on a ship with highly noisy background, we propose microphone co-linear array to increase microphone sensitivity. First, the normal shaft sound was recorded using single sensor, thereafter used as baseline. The cracks were intentionally introduced to the shaft with depth 0.25, 0.5, and 0.75 diameter of the shaft respectively. The sound mixture was separated using frequency domain independent component analysis (TFICA) and then, compared to the accelerometer. The results showed that the measurement accuracy was increased from one sensor to the array and comparable to the direct measurement. These results suggest that the proposed technique may be used as an easy-to-deploy vibration monitoring in a noisy and hazardous engine room.

1. Introduction

Recently, acoustic emission (AE) receives considerable attention for non-contact mechanical failure on a rotating machine because it may operationally simpler than that of the direct measurement [1]. However, the main problem is the difficulty to extract a crack sound of a failed rotating part of the machine due to highly adverse environment, particularly in an engine room. In this study, we propose a blind source separation (BSS) technique using microphone array to separate a crack signal of a rotating shaft from a mixture without knowing information sources and without knowing how the mixing process. The combination of loads bending, longitudinal and torsional vibrations in rotating shafts had been studied by [2], wherein the frequency of torsional excitation force was equal to the natural frequency of the bending load on the rotation axis of the crack.

The focus of this research is on the overdetermined case because with the increasing number of sensors, information signals are overcomplete. The purpose of this research is to use tFBSS (Time-Frequency Blind Source Separation) with Spatial Wigner-Ville Spectrum (SWVS) estimation approach. When compared with the underdetermined case, one of the advantages of this overdetermined case is in
its data processing or computing. For the overdetermined case, the settlement matrix easier where multiplication is not square m x n matrices where m ≥ n can be solved by joint diagonalization. Another characteristic in this case, namely the redundancy due to the number of sensors is more than the amount of the source. So that the necessary reduction of such redundancy. This is so that the output of the signal estimate equal to the number of sources and can be identified according to the original signal source.

The contribution of this paper is the following.

- The first goal to be achieved in this research is able to reduce redundancy signal (same signal) to the joint diagonalization in this tfBSS algorithm that estimates the output signal has the same amount to its source and has the same characteristics with the source identification.
- The second aim is to test the hypothesis whether the algorithm is tfBSS mixed signal (convolutive mixtures) of several emission engines with different characteristics can be separated.

This paper is organized as follows. In Section II, we formulate the BSS problem and list all required assumptions. In Section III, we outlined the methodology on this research. In Section IV, we present the result of baseline and mixed signals, separation of signals with tfBSS.

2. Measurement Method

2.1. BSS (Blind Source Separation)

Blind Source Separation Method is a method used to separate the mixed signals from multiple sources blindly (without knowing the mixing process) [1]. This method can be used for the overdetermined case / number of sensors is more than equal to the number of sources (m ≥ n), determined cases / number of sensors is less than the number of sources (m < n) and the cases determined / number of sensors equals the number of source (m = n). In this study, the BSS is focused on solving the overdetermined case by taking tfBSS algorithm (time-frequency Blind Source Separation). Algorithm other in the often discussed in this BSS is ICA. BSS method that addresses the algorithm ICA (Independent Component Analysis), can be found in references [11,12,13]. In this section, the BSS method described by taking the case determined that the BSS method of explanation can be understood more easily. As seen in Fig. 1, there are two sources of sound from the speaker 1 and speaker 2 will be received by the microphone 1 and microphone 2 so happened that the sound mixing mixture 1 and mixture 2. In this there are two sound mixing techniques and mixing is convolutive mixtures of line instantaneous mixtures. The results of this mixing will be processed by the BSS to be separated in order to be like the original single sound signal.

The results of the separation of sound signals or output signals of this BSS are separated signal 1 and separated signal 2. The BSS scheme can be seen in Fig. 2, showing that there are 4 filters mixture of h. (the source signal 1 received by microphone 1), h (source signal 2 received microphone 1), h (the source signal 1 received microphone 2), and h (source signal 2 received microphone 2). Further mixing was separated and denoted by the symbol W, W, W, and W. The results of this separation are called the signal estimate and denoted is y and y. From Fig. 1, tfBSS will be applied on the unmixing filters BSS algorithm.
2.2. Time-Frequency Blind Source Separation Steps

1. Whitening Data
The first stage in the separation of mixed signals that whitening the data from the sensor signal or the signal observation. In illustration, a data whitening process is illustrated in Fig. 5. The mixed signal that has not undergone a process called the original distribution whitening. From the figures can be seen the results of the original two-dimensional distribution of the oval-shaped or oval. After the whitening process is applied then the image that originally had an oval, a smaller image circle (shown in red). Image circle is a representation of the signal that has undergone a process of whitening. Blind source separation works well under Gaussianity and Independent. Subsequently, after data whitening process is completed then forwarded to the rotation or rotation.

2. Calculating STFD (Spatial Time Frequency Distribution) from the sensor signal which has undergone a process of whitening.

Here is the equation SWVS

$$SWVS_{xx}(t,f) = E[D_{xx}^{wv}(t,f)]$$  \hspace{1cm} (2.1)

where SWVD of the sensor signal which has undergone a process of whitening. SWVD equation itself is defined as follows

$$D_{xx}^{wv}(t,f) \triangleq \int_{-\infty}^{\infty} x(t+\frac{\tau}{2})x^H(t-\frac{\tau}{2})e^{-j2\pi ft}d\tau$$  \hspace{1cm} (2.2)

From the above calculation, the results will be obtained based on the estimated STFD is as shown in fig. 7. In the figure, the frequency and time can be displayed directly to a specific frequency can be determined at any given time.

3. Calculating Criterion and Collecting Single Auto Term.

Before determining the location of Single Auto Term, required calculation of the criterion first. The calculation of this criterion can be obtained from equation (2.3).

$$C(t,f) \triangleq \frac{\max_{k} \lambda_{k}(t,f)}{\sum_{k=1}^{p} \lambda_{k}(t,f)} = 1$$  \hspace{1cm} (2.3)

From equation (2.3), non-zero diagonal matrix obtained should only be one. So that non-zero eigenvalues to be obtained was only one. To obtain this value, then the above equation approximated by equation (2.4)

$$C(t,f) \approx \frac{\max \{|\text{eig}[D_{xx}^{wv}(t,f)]|\}}{\sum \{|\text{eig}[D_{xx}^{wv}(t,f)]|\}}$$  \hspace{1cm} (2.4)

where the criterion is the ratio between the maximum eigen value of the diagonal matrix with the total number of eigenvalues diagonal matrix itself. Physical meaning of the calculation of this criterion is actually to get the energy of each signal. The highest mean energy value close to the original signal are compared.

$$\text{If} \left( \frac{\max \{|\text{eig}[D_{xx}^{wv}(t,f)]|\}}{\sum \{|\text{eig}[D_{xx}^{wv}(t,f)]|\}} > \varepsilon \right)$$  \hspace{1cm} (2.5)
then \((t, f)\) is the position of \textit{Single Auto Term.}

From equation (2.5), the threshold value of \(\varepsilon\) in the interval \([0,1]\). For values closer to 1, it will be selected as a candidate in the joint diagonalization. From these intersection between the two signal sources is a diagonal matrix so that the necessary selection criterion for determining the position of \textit{Single Auto Term}. At these selections there were two assumptions, namely instantaneous mixture and superposition. Election SAT (Single Auto Term) with additive term may be less complex than the superposition (sum signal) because the combination to find a mate with each other less than superposition. This needs to be done because the process is required permutation BSS method, sign, and scaling (scaled).

4. Joint Diagonalization (JD)

Joint Diagonalization technique is the most important step in the separation of the voice signal from the sensor is larger than the number of sources \((m > n)\), because in this technique, the original matrix is not square can be a square matrix. Here is the equation to solve the joint diagonalization

\[
\mathcal{D}_{xx} \approx \mathbf{U} \mathcal{D}_{ff} \mathbf{U}^H \tag{2.6}
\]

where

\[
\mathcal{D}_{xx} \equiv \hat{W} (\mathcal{D}_{xx} - \sigma^2 I_m) \hat{W}^H \tag{2.7}
\]

From equation (2.7), \(I\) an identity matrix while \(\sigma\) is the variance. If the value of the variance here is zero, then the multiplication between the variance and the identity matrix is zero as well. While is a hermitian matrix estimation in which this matrix when multiplied by another matrix will produce an identity matrix. Thus, obtained by multiplying the identity matrix with diagonal matrix, the result is a diagonal matrix itself. So, to find the inverse matrix can be easily done.

2.3. Reduction of Redundancy

Reduction of redundancy required in the selection of code where some information will be stored and some others deliberately discarded but does not reduce the required information (Barlow, 2001). The main focus of this idea, but actually for the computational efficiency without losing much information. Therefore, the necessary reduction of redundancy if the information is transmitted to other locations like. This is done for memory efficiency. This is an aspect of Shannon's formula, published in a clear and important in communication engineering in which the captured information obtained from the detection sensor redundancy in the form of a small and dense. The reduction of redundancy can be further subdivided and displayed in the form of levels (Barlow, 1959). This can be illustrated as in fig.9.

In reference Scarpiniti Michele (2010) is said also that one of the assumptions and limitations of the BSS is an unknown mixture matrix is a square matrix. If the matrix is not square then the matrix is the result of redundant mixture. In this case, redundant this mixture can be removed so that the matrix can be a square matrix. The technique eliminates this redundancy is mathematically described in a paper Lars Omlor, Martin Giese (2007).

3. Measurement Setup

In total, six water pumps were used. On each pump was intentionally damaged with two damages of unbalance, bearing fault and misalignment. First of all, we measured the so-called baseline. The baseline was basically one pump with one damage only. The pump was in normal, bearing fault, misaligned and
unbalanced, respectively. The baseline was used to validate the sound pattern of the damages. In recording of the baseline signal, the sampling frequency used is 44100 Hz. The baseline signal was downsamled to 256 Hz with data length of 1024 to reduce computational complexity. The results of this baseline recording signal will serve as the ground truth for MSE calculation with the signal estimation result.

4. Results and Discussion

4.1. Mixed Signal Data

Furthermore, retrieval of data recording performed for the number of sensors is greater than the amount of engine noise signal sources. Configuration used to take a maximum of 4 sensors and 3 sources. By positioning the microphone sensors placed parallel with the engine when recording sound source sound signal. This meant that the sound signal from a microphone right in front of it can receive signals from a source with a strong engine but still receive the signal of other sound nearby in order to avoid the phenomenon of spatial aliasing. In this research, the configuration used is the number of sensors (microphones) is greater than or equal to the number of sources (engine pump).

4.2. Instantaneous Linear Mixture Separation

The results of the estimated signal and the TFD of 4 sensors and 3 sound sources of this pump can be seen in Fig. 4. In the figure, the frequency and time is plotted in a 2D (two dimensional) where the frequencies are shown the frequency normalization. In the figure, the color shows the magnitude of the amplitude (dB). As the colour goes toward red means the power is getting higher, while for the blue, then the amplitude gets smaller. To determine the frequency of normalization of the estimated pump, characterized by the greatest amplitude (red) are depicted resemble a horizontal line.
The window analysis was also conducted where we compared between the Hamming and Blackman Harris window. The results of the normalized frequency of the pump bearing fault 0.7, 0.02 normal pump, and pump unbalance 0.1, respectively. For the Hamming window had loss of 1.78 while the Blackman-Harris 0.83.

5. Conclusion

Mixed sound signals were successfully separated by the method of time frequency blind source separation and redundant signals from the sensors successfully reduced to only one signal at the output signal due to the estimated number of sensors greater than the number of sources. With this tfBSS method, separation of mixed sound signals (instantaneous linear mixture) is better than the mixed sound signal (convolutive mixtures) with MSE score. The results obtained from the TFD estimates was with the MSE of the Bearing Fault 0.17, 0.1 Normal pumps and pump unbalance 0.16, respectively.

References
[1] Fevotte, Cedric., Doncarli, Christian. “Two Contribution to Blind Source Separation Using Time-Frequency Distribution”. IEEE Signal Processing Letters vol.11, no.3, March 2004.
[2] A. Belouchrani and M. G. Amin, “Blind Source Separation Based on Time-Frequency Signal Representations”. IEEE Trans. Signal Processing, vol. 46, pp. 2888–2897, Nov 1998.
[3] A. Belouchrani, K. Abed-Meraim, M. G. Amin, A. M. Zoubir. “Joint Anti-Diagonalization For Blind Source Separation”. in Proc. ICASSP, vol.5, 2001, pp. 2789–2792.
[4] A. Belouchrani, K. Abed. Meraim, J-F. Cardoso dan E. Moulines, “A Blind Source Separation Technique Based on Second Order Statistics,” IEEE Trans. Signal Processing, vol.45, pp. 434-444, Feb 1997.
[5] A.Holobar, C. Févotte, C. Doncarli, dan D. Zazula, “Single Autoterms Selection for Blind Source Separation in Time-Frequency Plane,” in Proc. EUSIPCO, vol.1, 2002, pp 565-568.
[6] Barlow, H.B. “Sensory Mechanism, The Reduction of Redundancy, and Intelligence.” NPL Symposium on the Mechanization of Thought Process. No.10, pp. 535-539, HM Stationery Office, London, (1959).
[7] Barlow, H.B. “Redundancy Reduction Revisited.” Network : Comput. Neural Syst. 12 (2001) 241-253, Institute of Physics Publishing.
[8] L. Omolr, M. Giese. 2006. “Blind Source Separation for Over-Determined Delayed Mixtures.” Laboratory for Action Representation and Learning. Department of Cognitive Neurology. University of Tübingen, Germany.
[9] J. P. Nadal, N. Parga. 1997. “Redundancy Reduction and Independent Component Analysis : Conditions on Cumulants and Adaptive Approches.” Laboratoire associé au C.N.R.S. (U.R.A. 1306), à PENS,et au Universités Paris VI et Paris VII.
[10] L.Cohen. “Time Frequency Analysis.” Prentice Hall PTR Englewood Cliffs, New Jersey, 1995.