Time-Frequency Independent Component Analysis for Multi-Damage Detection on a Rotating Machine

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Abstract. Maintenance of the plant machinery plays a crucial factor for maintaining continuity of industrial processes. This paper reported a development of an acoustic-emission-based (A.E) technique of identifying multi-damage to the machine remotely using two sensors. In implementation, we emphasized in the separation of sound signals emitted by multiple machines using Time Frequency Independent Component Analysis (TFICA) recorded with a microphone array using the technique of mixing assuming a single source. Overall this study aimed to identify the unbalance, misalignment and bearing faults. Each machine had simultaneously two different damages, i.e. the bearing fault and unbalance, unbalance and misalignment, and bearing fault with misalignment. Separation process was performed using several types of techniques, namely, time domain ICA, frequency domain ICA. Observations FDICA superior in separation rather than TDICA with high MSE values are: $1.7 \times 10^{-5}$. From the experimental results showed that the distance between the microphone so the shorter the distance the smaller the spatial aliasing occurs.

1. Introduction

Blind Source Separation (BSS) is a method that can be used to separate a signal from a mixture without knowing information sources and without knowing how the mixing process [1]. This method was originally used as a signal separation technique of the human voice (speech) or often referred to as cocktail party problem [2, 5]. From the research that the study of BSS was developed again but with a different object of research is the engine pump. Research on the engine pump has been done by [7], but the algorithms used are BSS ICA (Independent Component Analysis) where the assumption in this method is to have the characteristics of independence and non-Gaussian for the signal source. The purpose of this research is the BSS algorithm to be used is tBSS (Time-Frequency Blind Source Separation) where the base used is the TFD (Time Frequency Distribution) with SWVS estimation approach (Spatial Wigner Ville Spectrum). The fundamental difference between [7] was the configuration of the sensor and source. Another difference lies in the assumption of the signal mixing techniques. Mixing assumptions on the signal [7] is a linear instantaneous mixture or superposition, while [3, 4] assuming the mixing is convolutive mixtures (mixing convolutive). This research was carried out two experiments: first take convolutive mixtures and the second assumption is instantaneous linear mixtures. Mixing is instantaneous linear mixtures for tBSS is based on the paper [3]. While the assumption of convolutive mixtures has not been tested so that the necessary
research to find out how this influences tfBSS algorithm if the mixing is carried out in convolutive. 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 formulated the BSS problem and list all required assumptions. In Section III, we shown methodology on this research. In Section IV, we present the result of baseline and mixed signals, separation of signals with tfBSS, Voice Signal Convolutive Mixture and Instantaneous Linear, comparing with ICA and tfBSS methods. In Section V discusses the results of the separation of many sources of engine noise tfBSS obtained with this method compared with the results of sound source separation of many machines with the ICA method.

2. Measurement Method

2.1. Mixture separation

The aim is to obtain the original sound of sources $s_1(t)$ and $s_2(t)$ whilst $Z^T$ is the output of the measurements $X^T \{1, 2\}$,

$$x_i(t) = A * z_i(t) + n(t), \quad (1)$$

where $x = [x_1, x_2, ..., x_m]^T$ represents the measured data, and $x_i, z = [z_1, z_2, ..., z_n]$ was the vector of sources. $A$ is a full rank matrix $A = [a_1 \ldots a_N]$ and the aim is to find $A^{-1}$, where $A^{-1}x = z$. The * notation indicates that the convolutive mixtures was assumed.

Furthermore [5],

$$\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} + \begin{bmatrix} n_1(t) \\ n_2(t) \end{bmatrix}, \quad (2)$$

and,

$$x_1(t) = a_{11}z_1(t) + a_{12}z_2(t) + n_1(t) \quad (2a)$$

$$x_2(t) = a_{21}z_1(t) + a_{22}z_2(t) + n_2(t) \quad (2b)$$

The problem is to estimate $A$ with information from the number of the sensors. With uncorrelated sources $z$, we may recast the problem into

$$s(t) = Wx(t),$$

where $W = A^{-1}$ then mathematically the problem became

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \end{bmatrix}^{-1} \text{ and } \begin{bmatrix} s_1(t) \\ s_2(t) \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}. \quad (3)$$

We used the Time Domain Independent Component Analysis (TDICA) and Frequency Domain Independent Component Analysis (FDICA) in speech sound separation [3]. The schematic of both techniques was shown in the Fig. 2 (a) and Fig. 2 (b), respectively.
2.2. Measurement Setup

2.2.1. Measured Samples. In total, six water pumps were used. On each pump was intentionally damaged with two damages of unbalance, bearing fault and misalignment as depicted in Table 1. First of all, we measured the so-called baseline. The baseline was basically one pump with one damage only. The pump was individually in normal, bearing fault, misaligned and unbalanced, respectively. The baseline was used to validate the sound pattern of the damages.

| Experiment | Number of Microphones | Damages type       |
|------------|-----------------------|--------------------|
| 1          | 1                     | unbalance (4 gr)   |
|            | 2                     | bearing fault      |
| 2          | 1                     | unbalance (8 gr)   |
|            | 2                     | misalignment (1 mm)|
| 3          | 1                     | Bearing fault      |
|            | 2                     | misalignment (3 mm)|
| 4          | 1                     | unbalance (4 gr)   |
|            |                       | misalignment (2 mm)|

At the Table 1, there were four experiments were set with different types of damages on one water pump. For example, experiment 1 the damages were one pump with 4 grams additional mass added to the impeller to introduce unbalance, and the bearings were intentionally damaged by hammer. The misaligned in mm were from the eccentricity of the rotating shaft. The number of sensors in the array was either one microphone and two microphones to compare the accuracy of the separated mixtures.
Fig. 3 depicts the experiment procedures of which the one pump emitted two distinct sounds of damages simultaneously \( S_1(t) \) and \( S_2(t) \) and recorded by one or two sensors. Using either TFICA and TDICA the estimates of \( y_1(t) \) and \( y_2(t) \) were obtained. When two microphones were used, the spatial aliasing limit were also tested by placing the microphone distance to each other from 10, 20 and 30 cm, respectively.

2.2.2. Laboratory Arrangement. The mini plant was set up inside a semi-anechoic chamber as shown the Fig. 5.

![Figure 5. General arrangement of the measurement setup.](image)

2.2.3. Measurement Procedure. Sound data from Panasonic GP - 129 water pump with 2950 rpm rotational frequency with 4 different mounted on the table (shown in Fig.5). Then Behringer XM1800S microphone as a sound sensor with characteristics and cable jack female type, while the interface used as an analog data converter to digital data is USB DAC Multi Channel (M-Audio Fast Track Ultra) with 2 inputs. Adobe Audition 1.5 were used to record the digital samples and saved with .wav (PCM) format. We set the recording with mono, 24-bit (recording depth), 24-bit (audio mix down), and 44100 Hz sampling frequency. To reduce computational complexity the audio files were downsampled to 16000 Hz. For separation, we used natural gradient algorithm with 100 iteration number, 0.00001 step and 30 process-block.

2.2.4 Mean Square Error measurement. MSE is a method used in statistics as a comparison between the estimated spectrum of the estimated signal with the signal source (baseline signal). The equation used in calculating the value of MSE is as follows:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (S - Sc)^2
\]

where,
- MSE = Mean Square Error
- \( n \) = number of samples
- S = original signals (baseline)
- Sc = signal estimation
3. Measurement Results

3.1. Baseline
Measurement results showed that the spectral based patterns of baseline were in good agreement with ISO 13373-2:2016 [6].

![Figure 6. Spectral pattern of normal pump (left) and unbalance with 4 grams added mass (right).](image)

As shown in Fig. 6 the normal pump spectrum is at 50 Hz which is in agreement to the rotation speed of the pump. The amplitude of the normal pump is also low which implies that the normal pump vibration is low. On the other hand, the amplitude of the unbalanced increased significantly compared to the normal. The location of the main spectrum remains the same at 50 Hz.

For the configuration of 2 sensors and one source with two simultaneous damages was conducted. The microphones position placed 15 cm to the pumps and distance between microphone is 10 cm, 20 cm, 30 cm, respectively. This is done in order to test the limit of spatial aliasing. The results were tabulated in the Table 2 and Table 3, respectively.

| Pump # | Damages          | MSE FDICA 10 cm | MSE FDICA 20 cm | MSE FDICA 30 cm |
|--------|------------------|-----------------|-----------------|-----------------|
| 2      | Unbalance (4 gr) | 5.05x10^{-5}    | 5.7x10^{-5}     | 9.3x10^{-5}     |
|        | Bearing fault    | 2.2x10^{-5}     | 4.5x10^{-5}     | 6.5x10^{-5}     |
| 3      | Unbalance (8 gr) | 4.4x10^{-5}     | 4.9x10^{-5}     | 5.3x10^{-5}     |
| 4      | Misalignment 1 mm| 5.3x10^{-5}     | 5.8x10^{-5}     | 6.6x10^{-5}     |
|        | Bearing fault    | 4.4x10^{-5}     | 5.4x10^{-5}     | 6.7x10^{-5}     |
| 5      | Misalignment 2 mm| 1.8x10^{-5}     | 3.4x10^{-5}     | 5.7x10^{-5}     |

Table 2 shows the MSE of the estimates of two sensors and compared to the baseline. Interestingly, the MSE of the estimates were significantly low. These results suggest that the technique may have accurately estimate the simultaneous damage on one pump.

Table 3 shows the MSE of the estimates of two sensors and compared to the baseline. In this experiment, TDICA showed lower accuracy in term of MSE compared to the TFICA, particularly the estimate of two simultaneous damages. Therefore, the frequency domain separation outperforms the time domain technique.
### Table 3. MSE TDICA

| Pump # | Damages                  | 10 cm   | 20 cm   | 30 cm   |
|--------|--------------------------|---------|---------|---------|
| 2      | **Unbalance (4 gr)**     | 8,7x10\(^{-3}\) | 8,7x10\(^{-3}\) | 9,4x10\(^{-3}\) |
|        | **Bearing fault**        | 5,2x10\(^{-3}\) | 5,2x10\(^{-3}\) | 6,8x10\(^{-3}\) |
| 3      | **Unbalance (8 gr)**     | 7,9x10\(^{-3}\) | 7,9x10\(^{-3}\) | 7,9x10\(^{-3}\) |
|        | misalignment 1 mm        | 22x10\(^{-3}\) | 24x10\(^{-3}\) | 27x10\(^{-3}\) |
| 4      | **Bearing fault**        | 22x10\(^{-3}\) | 22x10\(^{-3}\) | 7,4x10\(^{-3}\) |
| 5      | **Misalignment 3 mm**    | 1,1x10\(^{-2}\) | 1,1x10\(^{-2}\) | 1,2x10\(^{-2}\) |
|        | **Unbalance (4 gr)**     | 1,3x10\(^{-2}\) | 1,3x10\(^{-2}\) | 1,7x10\(^{-2}\) |
| 5      | **Misalignment 2 mm**    | 1,2x10\(^{-2}\) | 1,2x10\(^{-2}\) | 1,6x10\(^{-2}\) |

### 4. Conclusion
Acoustic emission (AE) based vibration measurement was performed in semi-anechoic chamber by simulating a rotating machine with two simultaneous damages. The time-domain and the frequency-domain independent component analysis techniques that previously used for speech mixture separation were proposed to separate mixtures with an array of two microphones. The results showed that the TFICA accuracy in MSE outperformed the TDICA significantly. The results are encouraging for field test in the on-going measurement in the presence of background noises. This may be used for alternative measurement where contact vibration measurement poses a hazardous threat to the human operator.

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