Separation of Acoustic Signals on a Compressor Using FastICA

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***Abstract*— Separation of mixed signals has been extensively studied for telecommunications, health, damage analysis, and others. This research focuses on the separation of acoustic signals to support the analysis of engine conditions. The compressor engine is the object of this research. Mixed signals will be separated using FastICA. The acoustic signal from the compressor engine parts is mixed with synthetic mixing and real mixing. Separation results will be evaluated through LSD and SDR values. Two machines with normal bearing condition and bearing fault condition successfully separated well in synthetic mixing with the largest SIR value was 5.60dB and the smallest LSD was 0.510.**

Keywords*— *BSS, FastICA, Compressor Faults

I. Introduction

Compressors are machines that play a role in increasing fluid pressure so that the flow of a process in the industry is as expected. Machine failure analysis is needed to support the operation of the machine. Faults analysis is commonly done by analyzing the vibration spectrums.[1]. The vibration changes generated by the compressor can cause the acoustic emission changes generated by the machine. An acoustic emissions can be used as an alternative method for faults identification in the industry[1][2]. Source signal that is interfered with other signals will make it difficult to determine the condition of the machine. Limitations in obtaining the original signal from each source encourage the need for signal separation.

Independent Component Analysis (ICA) is a popular method of signal separation. This method has been popularized by Hyvarinen et al[3]. One of the conditions that must be met in using this method is component independence[3-5]. The signal to be separated must be a non-Gausian signal. The ICA method separates mixed signals through statistical signal processing where there are several usable ICA models such as Time Domains ICA (TDICA), Frequency Domains ICA (FDICA), Multistage ICA (MSICA), and Fast Fixed-Point independent component analysis (FastICA)[3].

In a previous study, the separation of voice signals using the ICA method can be performed on cooling water pump in both the time domain (TDICA), as well as the frequency domain (FDICA) [4]. The same method can also distinguish the sound signals with background noise at PT Gresik Power Indonesia. The research comparing several ICA algorithms such as FDICA, TDICA, Time-Frequency ICA (MSICA1), Frequency-Time ICA (MSICA2), and FastICA found that the sound signal separation quality improved with FastICA algorithm [6]. FastICA is also used by Setiawan, succeeded in reducing the noise signal [5]. Another research using FastICA algorithm was conducted by Syarif[7]. The method successfully performs separation of the mixed audio signal. Comparison of bioacoustic signal separation methods such as NMF, PCA, and FastICA has been carried out by Hassan et al[8]. The bioacoustic signal was successfully separated by FastICA well compared to other methods based on SDR, SIR and SDR values. The equation used is an instantaneous mixing equation[8]. In this study, we use the blind source separation method with the FastICA algorithm to separate the mixed signal with the microphone as a sensor to record acoustic emissions. Separation results from synthetic mixing and real mixing will be compared in this study.

II. Theory

A. Blind Source Separation

Signal separation without known source information and the process of mixing the signal is called blind source separation. The concept of blind source separation is the basis of the ICA method. Simply the convolutive equation is as follows:

$$x(t) = \sum_{i=1}^{n} A(i).S(t-i) \tag{1}$$

where
x (t) : the result of mixing
A : the matrix containing the mixing component
S : the matrix containing the source constituent components.

Separation of the mixed signal is done by inverse of matrix A, S will be obtained which is the source signal in the frequency domain[3]

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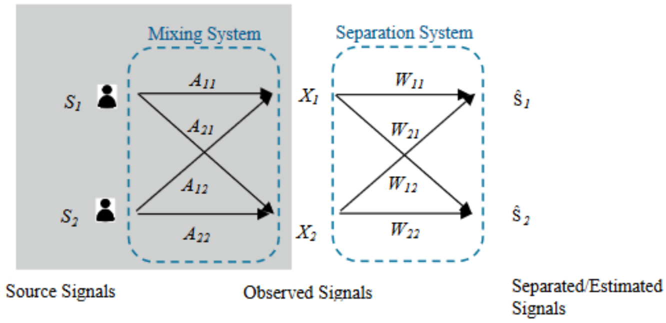


Fig.1. The concept of BSS[8]

B. FastICA

Fast Fixed-Point ICA (FastICA) is an algorithm used to separate signals. FastICA is the development of the ICA method. Where the FastICA algorithm is faster convergent than other algorithms. There are two stages in this algorithm: pre-processing stage and processing stage.

Pre-processing stage is a step that is done before the FastICA process, where the function of pre-Processing can simplify and speed up data processing. The pre-processing step is centering and whitening [4]. In the centering process, the mean data (x) will be changed to 0 (zero mean). The goal is to simplify and increase the speed at FastICA processing to achieve convergence, the equation as follows:

$$x_c = x - \bar{x} \tag{2}$$

where x is the mixed signal data, x_c is the mixed signal data that has undergone the centering process, and $\bar{x}$ is the mean of the data x.

At the whitening process, the result data from the observation will be processed so that the data will be a new vector that has no correlation with each other but still in the same data variant. The covariance matrix $\tilde{x}$ having the same value as the identity matrix, which is described in the equation:

$$E\{\tilde{x}\tilde{x}^T\} = I \tag{3}$$

The common method used in the whitening process is the eigenvalue decomposition (EVD) of the covariance matrix:

$$E\{xx^T\} = EDE^T \tag{4}$$

wherein the EVD method, the eigenvalues and eigenvectors of $\{xx^T\}$ will be observed through equations:

$$x\lambda = D\lambda \tag{5}$$

The matrix will be calculated eigenvalues and eigenvectors represented by x, the diagonal matrix of the eigenvalues and vectors is given by D, and λ is the eigenvector of the x matrix. Then the whitening process is done by calculating the whitening matrix shown in the equation: V is the whitening matrix and z is the whitened matrix[3][5][7].

$$V = ED^{-\frac{1}{2}}E^T x_c \tag{6}$$

$$z = Vx_c \tag{7}$$

After centering and whitening process, the data will be processed with the algorithm. The following is the stages of the FastICA algorithm:

1.Select an initial value of complex vector w(randomly)
2.Calculate the value of the new w, with the following equation

$$\{zg(w^T z)\} - E\{g'(w^T z)\}w \tag{8}$$

3. Normalize the value of the new w
4. Re-iteration step 2 until reach convergence

III. EXPERIMENTAL SETUP AND RESULTS

The research object used was a 15kW compressor engine with 3000RPM. Two machines from the object of this research are the inboard motor with normal bearing (S1) and inboard-male screw compressor with outer race bearing fault (S2). Fig.2 is a baseline signal recording. In the recording process we use 44100Hz as a sampling frequency. The frequency adjusts the frequency of the USB audio interface, while the frequency we use in the separation process is 8000Hz.

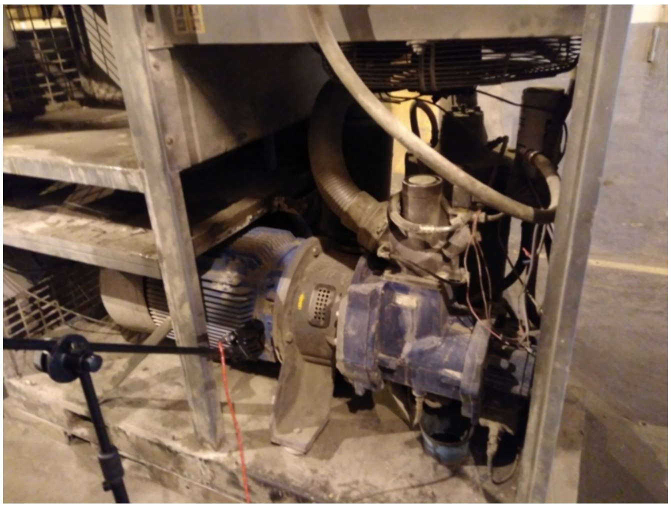


Fig.2. The example of S1 baseline recording

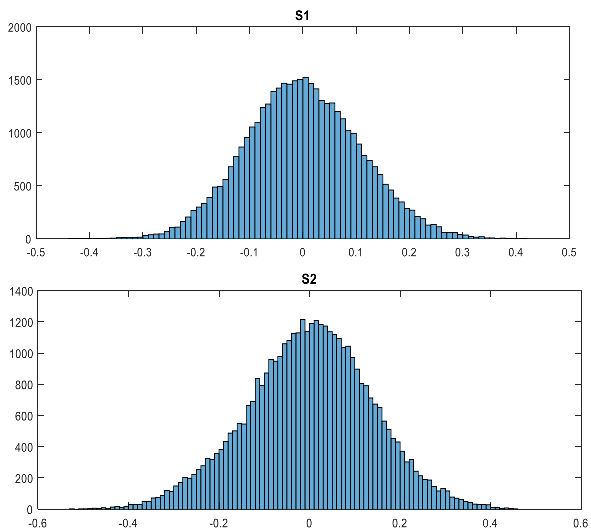
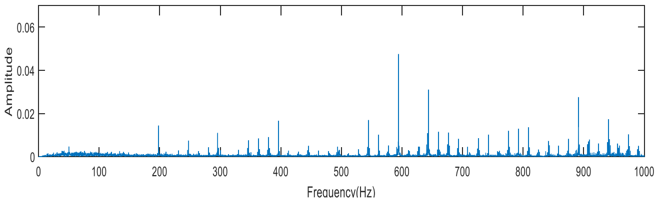
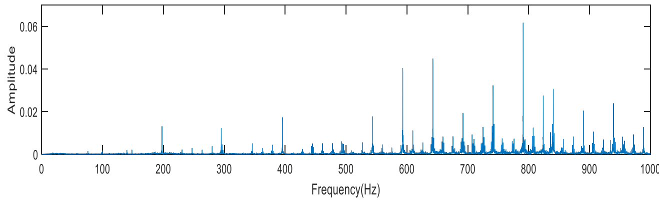


Fig.3. Histogram of baseline signals



(a)



(b)

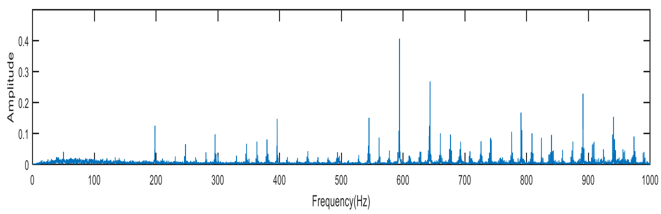
Fig.4. Baseline signals (a).S1 with normal bearing (b).S2 with outer race bearing fault

After the baseline signals for each machine are completely obtained, the next step is the independence test. The separation process can be carried out if the signal components are non-Gaussian distribution. Non-gaussianity can be known from the shape of the histogram, kurtosis, and etc. The S1 baseline signal has a non-Gaussian distribution with a kurtosis value is 2.93 and the histogram is shown in Fig.3. Non-Gaussianity is also shown by the histogram of the S2 baseline signal with a kurtosis value of 3.03. The spectrum of the two signals has a characteristic. Bearing damage in S2 is indicated by the presence of high amplitude at 800Hz. The presence of harmonic frequencies also indicates the damage[9]. After the independence criteria are fulfilled, the mixing and separation process will be carried out.

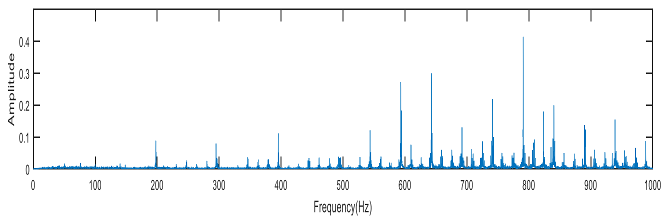
The two baseline signals that have been obtained previously will be mixed through synthetic mixing with average SNR value of 23.72dB. The mixing matrix A obtained is:

$$A = \begin{pmatrix} 0.7685 & 0.2315 \\ 0.3100 & 0.6900 \end{pmatrix}$$

Based on the results obtained, there is a amplification of the amplitude of the signal separation. The two spectra results from FastICA separation resemble the baseline signal spectrum shown in Fig.5.



(a)



(b)

Fig.5. Separated signals from synthetic mixing (a).S1(b).S2

Separation of signals with real mixing was carried out in this study. In the mixed-signal recording, we use 90cm as the distance between the sound source and the sensor, and 15cm as the distance between a pair of the sensor. The signal recording setup for real mixing is shown in Fig.6.

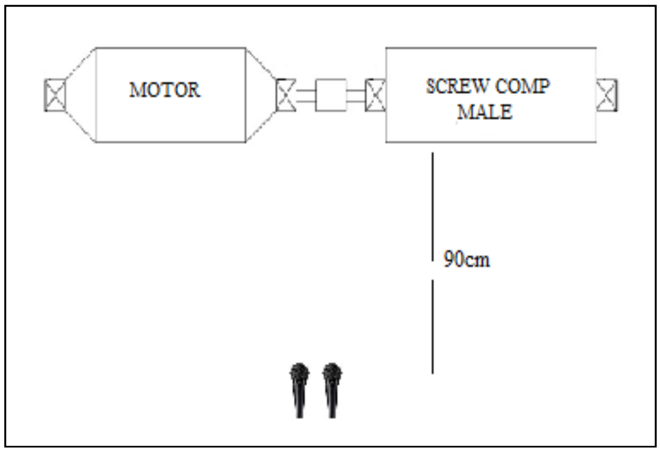
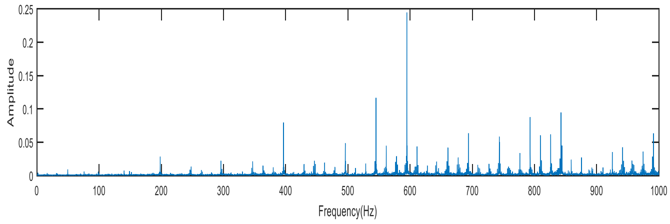
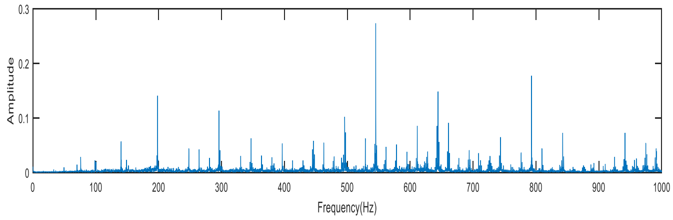


Fig.6. Illustration of mixed signal recording



(a)



(b)

Fig.7. Separated signals from real mixing (a). $\hat{S}1$ (b).$\hat{S}2$

The S1 baseline spectrum with normal bearings has high amplitude at 600Hz, 650Hz and 900Hz where in the $\hat{S}1$ spectrum of real mixing high amplitudes appear at 550Hz, and 600Hz. Although the estimated signal from the real mixing is distorted, the instantaneous frequency of $\hat{S}1$ is the same as the S1 baseline signal which is 600Hz. Bearing fault in the S2 baseline spectrum is indicated by the amplitude that appears harmonically at 550Hz, 600Hz, 650Hz, 700Hz, 750Hz, 750Hz, 800Hz, and 850Hz. The instantaneous frequency is at 800Hz. High amplitude in the $\hat{S}2$ spectrum of real mixing is seen at 550Hz, 650Hz, and 800Hz. Unlike the baseline signal, the instantaneous frequency of the $\hat{S}2$ spectrum is 600Hz.

For the performance test of signal separation, we use Log Spectral Distance (LSD) and Signal to Distortion Ratio(SDR). LSD use comparison between baseline frequency spectrum and estimated frequency spectrum. SDR is one of the parameters to test how well the separation results. SDR is obtained by comparing the energy of the baseline signal to the error of the baseline signal and the estimation signal. The higher SDR value indicates that the estimated signal does not occur much distortion so that it is more in accordance with the original signal. The smaller LSD indicates the estimation signal that is getting closer to the basline signal. Performance test results are shown in Table 1. The performance of the separation results from the synthetic mixing was higher than the real mixing. This is indicated by the SDR values of 5.60dB and 5.52dB on the Ŝ1 and Ŝ2 estimated signals. In real mixing, the estimated signal is distorted which can be caused by other noise that is active in the recording area so that it has an impact on the results. In a study conducted by Hassan *et al*., FastICA has a high performance in the simulation. The approach used is a linear instantaneous mixing[8]. The use of convolutive equations in this study represents the actual environmental conditions due to the delay component so that it differs from instantaneous mixing[3]. The result of separation by instantaneous mixing is better than convolutive mixing[10].

TABLE 1. Performance of the Signal Separation Results

No	Signal	SDR(dB)	LSD
1	Ŝ1-synthetic mixing	5.60	0.510
2	Ŝ2-synthetic mixing	5.52	0.563
3	Ŝ1-real mixing	-19.52	1.009
4	Ŝ2-real mixing	-15.46	1.054

IV. Conclusion

The FastICA method has been applied in separating acoustic signals from compressor machines. The convolutive mixing equation was used in this study. Two machines with normal bearing condition and bearing fault condition successfully separated well in synthetic mixing with the largest SIR value was 5.60dB and the smallest LSD was 0.510. The signal quality of the separation results in the real mixing is not as good as in the synthetic mixing. Varied environmental conditions and the application of adaptive methods will be of concern in future research.

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References

[1] Balerston, H. L, “The detection of incipient failure in bearings”, *Materials Evaluation*, Vol 27, 121-128, 1969

[2] Vinaya, Anindita Adikaputri, and Dhany Arifianto. "Multi-way array decomposition on acoustic source separation for fault diagnosis of a motor-pump system." International Journal of Electrical and Computer Engineering 7.6 (2017): 3052.

[3] O. Hyvarinen, “Independent component analysis: Algorithms and ahallications,” Neural Networks, vol. 13, nº (4 -5), p. 411 –430, 2000.

[4] Shen, Hao, Martin Kleinsteuber, and Knut Huper. "Local convergence analysis of FastICA and related algorithms." IEEE Transactions on Neural Networks 19.6 (2008): 1022-1032.

[5] Setiawan, I.B., Prasida, T.A.S., and Bazaleel, Michael. (2011), "NoiseReduction Application for Sound Quality Improvement in Audio Data Using FastICA Algorithm", Journal of Information Technology, Vol. 8, No. 2, p. 101-200.

[6] Ilham.Z. Risqi, and Arifianto, Dhany. (2012), "Performance Evaluation of Blind Source Separation Method on Cooling Water Pump Machine", Journal of POMITS Technique, Vol. 1, No. 1, p. 1-5.

[7] Syarif. (2008), Separation of Audio Signals Mixed Offline With Independent Component Analysis Algorithm, Thesis., Diponegoro University, Semarang.

[8] Norsalina Hassan, Dzati Athiar Ramli, “A Comparative Study of Blind Source Separation for Bioacoustics Sounds based on FastICA, PCA and NMF,” Procedia Computer Science, vol. 126, pp. 363-372, 2018.

[9] Felten, Dave. "Understanding bearing vibration frequencies," Electrical Apparatus Service Association (EASA), St. Louis, MO, 2003.

[10] Nion, D., Mokios, K. N., Sidiropoulos, N. D., & Potamianos, A, “Batch and adaptive PARAFAC-based blind separation of convolutive speech mixtures,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 18, no 6, pp. 1193-1207, 2010