

Research Article

The Effect of Number of Microphones to Amplitude Changes for Detect Crack on Rotating Shaft with Blind Source Separation-Independent Component Analysis Method

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Abstract: This study aims to determine the amplitude change due to the addition of the number of microphones to detect the cracking of the rotating shaft. This study presents the measurement of sound data from the cracked shaft which is one component of a simple transmission system. The sound signal emitted by the cracked shaft is very complex, low frequency and comes from various sources. Statistically, the sound signal is independent and based on this nature; the mixed signal can separate. The method to separate mixed signals is blind source separation without knowing the origin and process of a signal combined with Independent Component Analysis (ICA). One of the conditions that must satisfy in the BSS method is to know the number of source signals, but in practice, what happens is not specific and complicated. This study use variable is the number of microphones and the shaft speed. The results obtained are the use of microphone array of two, three and four can increase the magnitude amplitude of the estimation signal, while the increased of the shaft speed, the magnitude amplitude of the estimation signal also increased. Use of four microphones has of higher amplitude values than a single, two and three microphones. Moreover, the lowest mean square error value increases the microphone sensitivity. Implications of using microphones array to detect a crack that cannot measure by an accelerometer and avoid distortion on the rotating shaft.

Keywords: Amplitude, blind source separation, cracked shaft, independent component analysis, microphone array

INTRODUCTION

Blind Source Separation (BSS) is a method to separate mixed signals originating from various sound sources. This BSS method is blind without knowing the origin and process of the mixing signal. BSS was first introduced by Jutten and Herault (1991). The BSS method has applied to the field of monitoring structural conditions studied by Gelleet *al.* (2001). This study shows the basic principles of BSS and is applied to measure the vibrations of a rotating engine. The results indicate that the temporal BSS is useful for diagnosing machine failure. Zhou and Chelidze (2007) also apply the BSS method for identification using the Linear Normal Mode (LNM) method. There are two BSS algorithms considered in this study and is especially suitable for extracting LNM from vibration systems.

On to monitoring conditions field, some technologies have been used to diagnose machine

failures based on vibration signals (Huanget *al.*, 2009; Lakis and Mohammadi, 2012), but there are still limitations to detect failures. Sound features can be obtained and become information to diagnose machine failure. In practice, signals are typically a very low signal to noise ratio. The feature of the original sound signal obtains the uncorrelated must removed and the wavelet coefficient associated with the failing condition (Zhonget *al.*, 2006). They used the BSS technique to recover the wavelet coefficients of a monitored signal from complex signals. In a BSS application, the number of sound sources must determine first and the reconstructed wavelet coefficient can be used to make a failure diagnosis.

The BSS method consists of signal recovery from several of different sources that observed independently of the propagation medium. The source is assumed to be periodic and can model as the number of harmonic frequency sinusoids to separate the rotating engine

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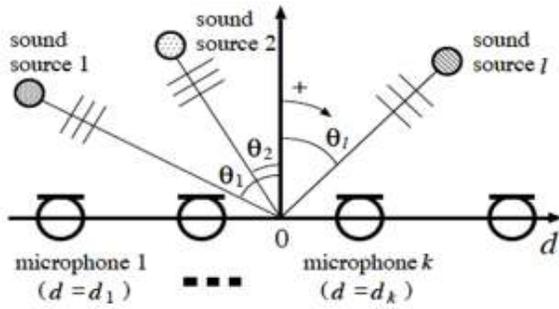


Fig. 1: Illustration of microphone array (Nishikawa, 2005)

signal (Serviere and Fabry, 2004). BSS used to monitor rotating machines such as water pumps (Popescu, 2010; Ypmaet *al.*, 2002).

The number of sources and number of sensors is an important part to consider in BSS applications. The number of sensors (M) less than the sum of source Signals (N) is called the under-determined BSS. Research that implements underdetermined BSS (Tang *et al.*, 2016) and the method offered is to combine the Variational Mode Decomposition (VMD) with FastICA to extract the roller compound feature. The proposed method is more efficient for separating the bearing outer-race defect and roller defect than the traditional envelope spectrum analysis. Moreover, through comparative experiments show that the proposed method has higher adaptability and practicability in separating active sound signals than the empirical mode ensemble decomposition method. The number of sensors (M) over the number of source signals (N) is called over-determined (Johoet *al.*, 2000).Based a background sensor with a low SNR then to improve the performance used the number of sensors more than the number of source signal under noisy conditions, faster convergence rates and a higher steady-state SINR can achieve.

The effect of source number estimation on the application of BSS has been investigated by Chuanchuanet *al.* (2017) in the condition over-determined and under-determined. They were applying the blind source separation algorithms based on natural gradient and equivariant adaptive source separation via independence in the condition over-determined and positive-determined. Moreover, for the condition under-determined, the mixing matrix estimation algorithm based on single source detection method in time-frequency domain is adopted for analyzing source number estimation's effect on mixing matrix estimation and statistics sparse decomposition algorithm is selected for analyzing the effect of source number estimation on signal separation.

Previous studies have suggested that the application of BSS Algorithms should usually know the number of sources. However, in practice, initially, the number of sources is not specific and complicated. The

fundamental difference in this study, the number of sensors determined without knowing exactly the number of sound sources with the assumption that the sound emitted at the time of the test model operated very complex and can not be determined correctly. In this study, the BSS-ICA method is applied to separate the mixed signal emitted by the cracked shaft rotation of the transmission system. The contribution given by the use of BSS-ICA method with microphone array is to know the amplitude change due to the modification of the shaft speed. A simple microphone array illustrated in Fig. 1 with the distance between microphones. The hypothesis in this study is if the number of the sensors and the shaft speed increased, the amplitude values would increase.

BLIND SOURCE SEPARATION-INDEPENDENT COMPONENT ANALYSIS

Statistically, the independent source signal means that one signal does not depend on the other. Based on the nature of this independence then the mixed signal can be separated into estimation signals. The method using this property is the Independent Component Analysis (ICA) that processes signals in the time domain and frequency domain.

The measured components of the sensor in time domain can model as:

$$x_j(t) = a_{j1}s_1(t) + a_{j2}s_2(t) + \dots + a_{jn}s_n(t)(1)$$

The Eq. (1), when written in vector-matrix form becomes:

$$x = As \quad (2)$$

Or:

$$x = \sum_{i=1}^n a_i s_i(3)$$

Equation (2) above is known as a model of Independent Component Analysis (ICA). The independent component s is a hidden part, in which the component cannot directly observe. The mixing matrix A is unknown, only the measured signal, x, is known. If Eq. (3) above is written in the form of a two-dimensional matrix then:

$$\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} * \begin{bmatrix} \bar{s}_1 \\ \bar{s}_2 \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \end{bmatrix} = \begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} * \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$$

The estimation signal is expressed by:

$$y = Wx(5)$$

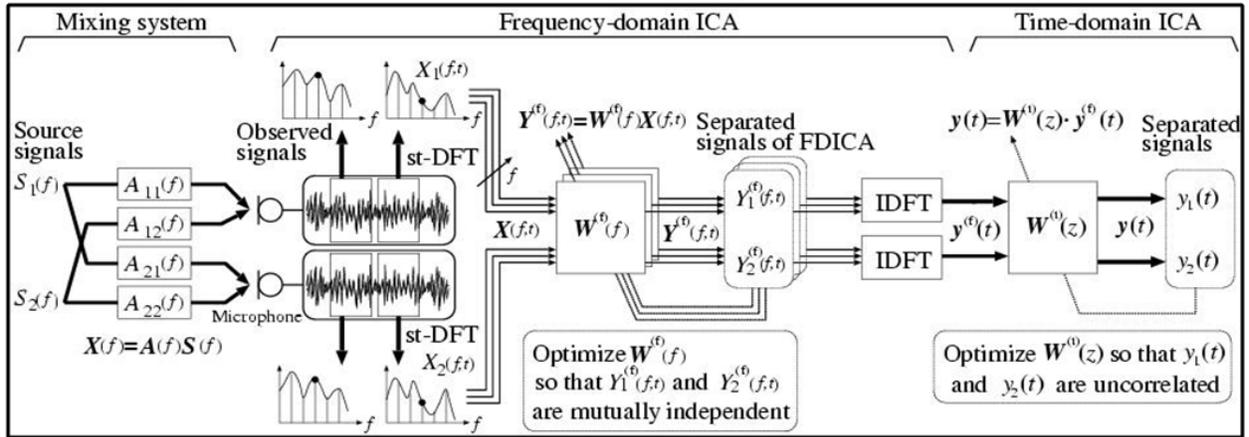


Fig. 2: Multistage ICA

where: $W = A^{-1}$

The main problem of the ICA method is to find the linear filter model W , where W is the inverse of the mixing matrix A . The accuracy of the selection of this model will affect the quality of signal separation. The signal analysis can perform in time and frequency domain. In the time domain, the signal represented by a waveform, where the axis x denotes the time and y axis represents the magnitude of the amplitude at each time t . In the frequency domain, a signal can represent a spectrum that represents the magnitude of each spectral component. The process of changing the waveform into this spectrum by transforming the signal with the Fourier Transform. If $f(t)$ is a signal in the time domain, then the Fourier Transform is:

$$G(j\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t} dt(6)$$

The computation of Fourier Transforms can be done quickly by the FFT technique (Fast Fourier Transform) which is a Discrete Fourier Transform (DFT) of vector x which calculated as follows:

$$X(k) = \sum_{j=1}^N x(j)\omega_N^{(j-1)(k-1)}(7)$$

$$x(j) = \frac{1}{N} \sum_{k=1}^N X(k)\omega_N^{-(j-1)(k-1)} \quad (8)$$

Where, the length of the FFT vector is N and $\omega_N = e^{\frac{-2\pi i}{N}}$. To restore in time domain then it can use Fourier Transforms as follows:

$$y(j) = \frac{1}{M} \sum_{M=1}^M u(m, l) e^{\frac{j2\pi(m-1)(k-1)}{M}}(9)$$

$k = 1, \dots, M$

k -th is the input of the l -th output channel, $y(k, l)$ equal to k -th point of a number of M -point Inverse Discrete Fourier Transform (IDFT) of l -th input channel.

Nishikawa *et al.* (2003) propose to use multistage Frequency Domain (FD-ICA) and time domain (TD-

ICA) analysis techniques to solve BSS-ICA problems. In within the time domain, the observed signals in which multiple source signals mixed linearly are given by:

$$x(f) = A(f)s(f)(10)$$

where, $X(f) = [X_1(f), \dots, X_K(f)]^T$ is the observed signal vector and $S(f) = [S_1(f), \dots, S_L(f)]^T$ is the source signal vector $A(f)$ is the mixing matrix which is assumed to be complex-valued.

Time Domain-ICA (TD-ICA) and Frequency Domain-ICA (FD-ICA) have advantages and disadvantages. FD-ICA simplifies the sum of convolution into instantaneous and easy reaching convergence in its iteration, while TD-ICA has a big convention near its optimum point and can eliminate full band signals where the assumption of signal independence usually retained. The proposed MS-ICA is showing in Fig. 2. Multistage ICA begins with source signal processing through FD-ICA mixing process, the signal observed in the frequency domain and the output signal of FD-ICA input to TD-ICA. Through the TD-ICA process, the signal is separated again into a TD-ICA estimation signal.

MATERIALS AND METHODS

This study was conducted on January-September 2014 at Semi Anechoic Chamber, Vibrastic Laboratory, Department of Physics Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia.

Materials: The test performed on a simple transmission system model. A model consists of an electromotor, clutch, two rollers bearing for support the test shaft and a radial mass. The material of the test shaft is steel DIN

17315A ST 41 and the dimension is length of 800 mm and 14 mm diameter. The crack of the test shaft made

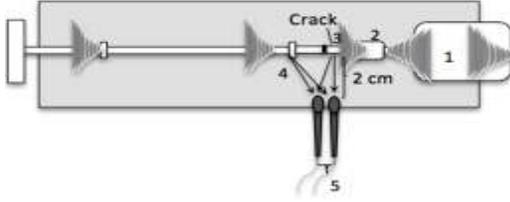


Fig. 3: Test model and microphone array

Table 1: The configuration of measurement at the shaft speed condition

No.	Shaft speed (rpm)	Microphone array		
1	500	Two	Three	Four
2	600			
3	700			
4	800			
5	900			
6	1000			

through wire cutting with the depth of crack 25% of the diameter.

Methods: As the system operates, each component emits sounds simultaneous. At the same time, the sounds for each component are difficult to recognize. The traditional way to distinguish signals from one another is by bringing the ear closer to the element. It is still there is a shortage with the limitations of human hearing. The blind source separation method is used to separate the mixed signal without knowing the origin and sound source process. Determined of baseline signal is an initial step to the application of blind source separation methods (Thenuet *al.*, 2017). On this study, baseline signal determined using a single microphone. There is some point measurement arranged linearly with interval distance 10 cm. The result shows that on 30 and 40 cm point have magnitude amplitude similar. After that, analysis conducted with a microphone located on crack location. The spectrum signal obtained have the same pattern of a signal on 30 and 40 cm point and have magnitude amplitude similar. Based on this result, the sound signal measured on crack location is baseline signal and used as a benchmark in identifying mixed signals that have separated and determined the quality of amplitude parameters from baseline signal and microphone array measurements. From Fig. 3 shown there are two microphones placed at a certain distance with the crack location (marked black in Fig. 3). Microphone 1 placed towards component 1 while microphone 2 placed to the left with a distance of 5 cm. At the sound measurement, sensor 1 and 2 will receive sound from all component. It is inevitable that each sensor can receive sound from other components. However, through the BSS-ICA Method, the mixed signal can be split into estimation signals that will compare with the baseline signal.

Experiment setup: The first step of the test is recording the baseline signal at the crack location. The test was performed on a test model using a test shaft with the depth of crack 25% (called the cracked shaft 0.25D). The sensor used is a super cardioid type microphone to be able to capture sound from various sources. After recording the baseline signal, the next test is the retrieval of the acoustic signal data using multiple microphone sensors. The number of sensors used is 2, 3 and 4.

The sensor connected to the breakout box of PCI sound card (Delta M-Audio) which has six inputs and six outputs. On each channel, simultaneous recording and each file stored with extension.wav (PCM). The sampling frequency is 44.1 kHz had taken by observing that the maximum frequency of the motor is 5000 Hz, to satisfy the Nyquist criterion and must be greater than or equal to twice the maximum frequency.

The recording process conducted at semi anechoic chamber. Figure 3 shown each microphone will receive a signal from each source. The distance between the sources of one and other sources is different, then there will be multi source effects that cause the occurrence of the phase caused by differences in mileage and angle of arrival. The difference in signal properties in the first microphone and the n -th microphone (where n is the integer and the number of sensors) sorted according to the statistical properties of the signal (independence). The arrangement of the number of microphones essentially superimposes the sound field at different points. One of the phenomena that should avoid the use of this microphone arrangement is the existence of spatial aliasing. To prevent this problem, a rule where the distance between microphones must be less than half the wavelength of sound. The minimum sound wavelength equals the maximum sound frequency, which the distance between microphones can determine. Rules of distance between microphones as follows:

$$d = \frac{\lambda_{min}}{2} \quad (11)$$

where, λ_{min} is the minimum wavelength of the sound source object (proportional to the maximum frequency). The speed sound is 330 m/s in the air at 0°C and the speed sound is 340 m/s in the air at 25°C.

$$d = \frac{\text{maximum frequency}}{\text{the speed of sound}} = \frac{16.67}{340} = 0.049 \text{ m} \\ = 4.9 \text{ cm}$$

Based on the distance rule between the microphones, the distance between microphones used in this test is 5 cm.

In this study, microphone array used is straight line arrays. The arrangement of the microphone array to find out how much influence the increasing number of sensors to the amplitude of the resulting signal. Signal

recording performed on rotating shaft with the shaft speed of 500-1000 rpm or 8.33 Hz-16.67 Hz. The signal recording configuration is showing in Table 1.

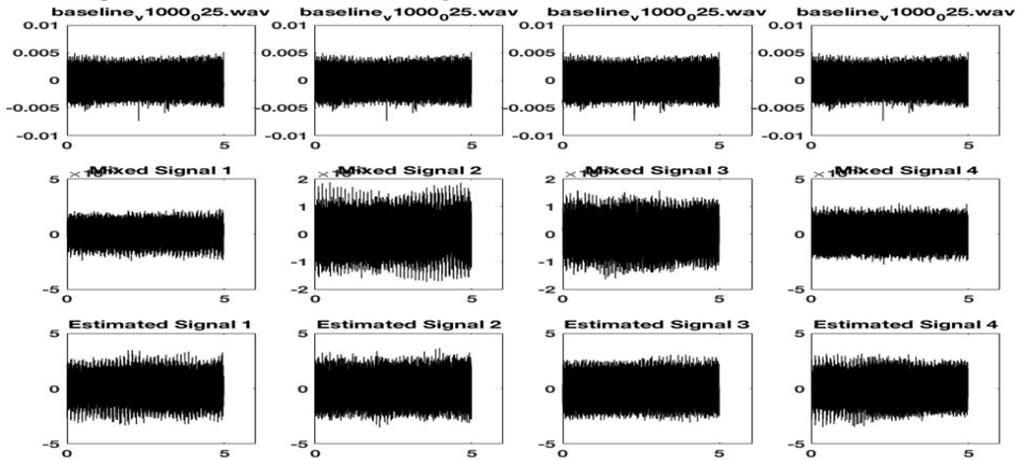


Fig.4: Waveform of baseline, mixed and estimated signal with four microphone at 1000 rpm

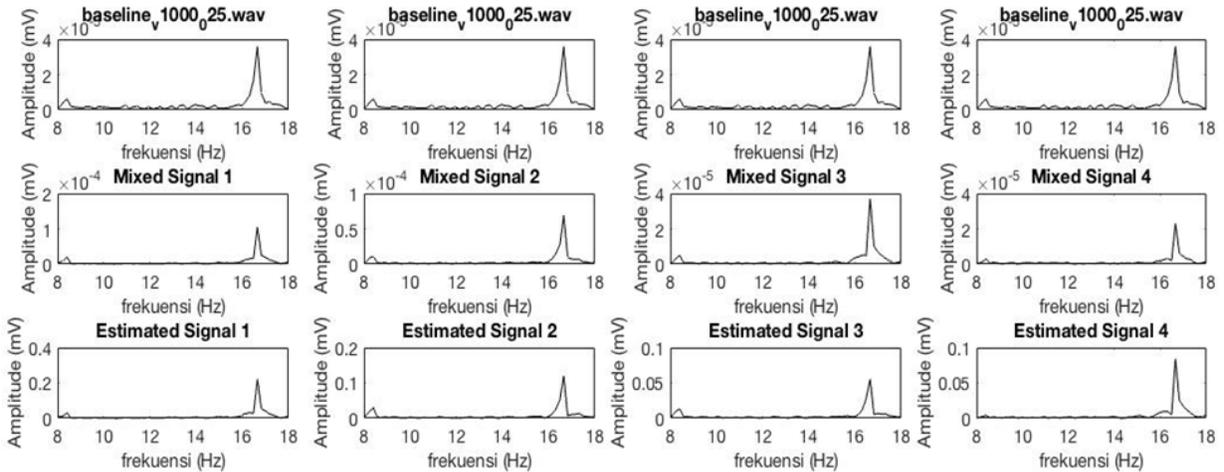


Fig. 5: FFT of baseline, mixed and estimated signal using four microphone at 1000 rpm

RESULTS AND DISCUSSION

When performing the test, two hypotheses want to prove in the data collection with this microphone array. The first hypothesis is the increment of microphone array then the signal amplitude in the graph plot will increase, the second is that increasing signal amplitude will follow each addition of the shaft speed.

The effect of the number of microphones: The signal input of microphone array processed using Time-Domain Independent Component Analysis (TD-ICA) method to generate estimation signal. The use of TD-ICA method has advantages such as taking all signals so that the independent characteristics reduced and the possibility of high convergence at the near optimal value. This section shows the results of processing on the cracked shaft 0.25D with 500 rpm to find out the amplitude change due to the increase in the number of

the microphone. Figure 4 shows the TD-ICA waveform of the baseline signal, mixed signal and the estimated signal by the measurement of four microphones. It appears that there is significant differences in the baseline, mixed and estimated signal. The fundamental difference can see in the baseline signal amplitude smaller than the estimated signal amplitude. The process of converting waveforms into spectral signals through Fast Fourier Transform show in Fig. 5. The magnitude of the estimated signal with the measurement of four microphones is higher when compared with the measurement of three microphones (Fig.6) and the measurement of two microphones (Fig. 7).

The measurement result of microphone array at the cracked shaft at 500 rpm (first hypothesis) shown in Fig. 8. The figure shows an amplitude change in the estimated signal due to the increase in the number of microphones at a speed of 500 rpm. This case

concludes that the more microphones used in the array will cause higher sensor sensitivity. However, in this case, the use of sensors and regression equations apply to four sensors only because when the sensors more

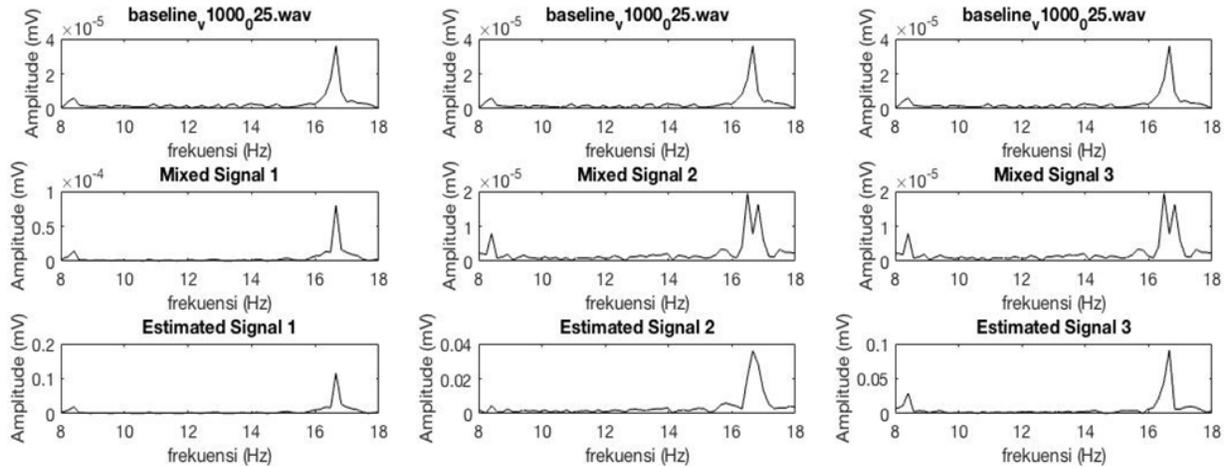


Fig. 6: FFT of baseline, mixed and estimated signal using three microphone at 1000 rpm

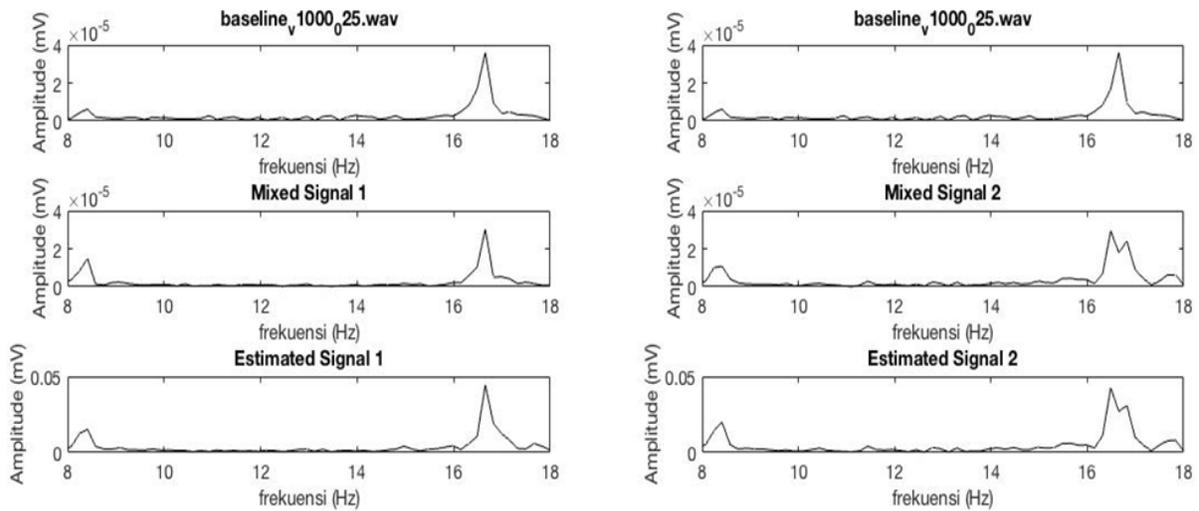


Fig. 7: FFT of baseline, mixed and estimated signal using two microphone at 1000 rpm

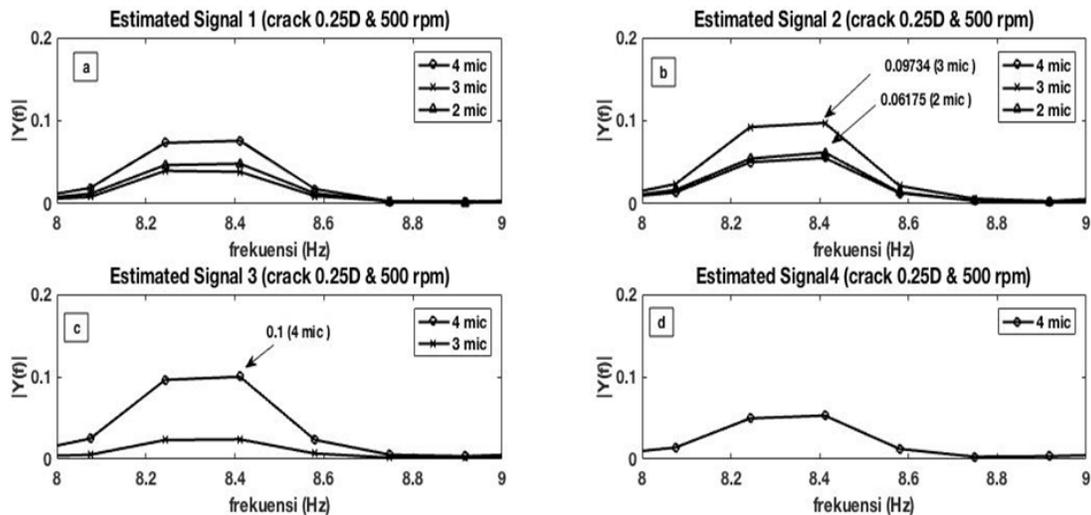


Fig. 8: Spectrum signal estimation microphone array (two, three and four microphone)

Table 2: The frequency and amplitude values of the cracked shaft 0.25D at the shaft speed of 1000 rpm (equivalent = 16.67 Hz)

Number of sensors	Frequency(Hz)	Amplitude
1 (baseline)	16.65	2.43 X 10 ⁻⁵
2	16.65	0.04447
	16.65	0.02704
3	16.65	0.01156
	16.65	0.03594
	16.65	0.09111
4	16.65	0.221
	16.65	0.1202
	16.65	0.0555
	16.65	0.08402

Table 3: MSE of the cracked shaft at 500 rpm

The cracked shaft	Shaft speed (rpm)	The number of microphone	MSE	
25 %	500	Two	MSE 1	0.063653
			MSE 2	0.058363
		Three	MSE 1	0.051072
			MSE 2	0.060397
			MSE 3	0.056053
		Four	MSE 1	0.047945
			MSE 2	0.066287
			MSE 3	0.048235
			MSE 4	0.058218

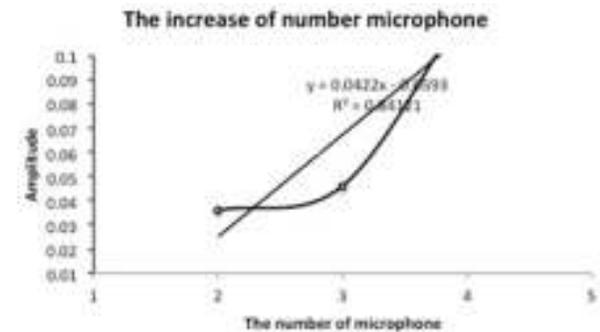


Fig. 9: The increase of amplitude due to the number of microphones

than four microphones, the distance between the microphone with the sound source will be farther away so it cannot capture the signal source.

In Fig. 8a and 8b describes the amplitude of the recording signal by two, three and four microphones. While Fig. 8c consists of two graphs because only compares the microphone array signals composed of three and four microphones. In Fig. 8d consists only of one spectrum signal with a composition of four microphones. The symbol graph Δ shows the result of signal processing using two microphones that have the highest amplitude value of 0.06175 (Fig. 8b). The symbol x is the result of signal processing of three microphones with the highest amplitude value of 0.09734 (Fig. 8b). The graph of o indicates the result of signal processing with four microphones with the

highest amplitude value of 0.1 (Fig. 8c). From the value shown is known that each increase in the number of microphones results in an increased amplitude value. Following the theory of microphone array that explains that the number of microphones increasingly the quality of the sound capture will be better. This process occurs because the increase in the number of microphones is directly proportional to the gain of the microphone.

The signal frequency of the baseline and microphone array has the same value of 16,65 Hz listed in Table 2; this shows the compatibility between the baseline signal and the estimation signal. Table 2 also displays the estimated signal amplitudes of each microphone array condition. Figure 9 illustrates the amplitude change caused by the increment of the number of microphones used in the microphone array. The relationship between the increment of the microphone with the amplitude indicated by the regression equation is 0.0422x+0.0593. This equation shows that each addition of one microphone will increase the signal amplitude by 0.0422 mV. Results obtained that the amplitude values of microphone array yield greater regression coefficient values than using a single microphone.

The effect of increased shaft speed: The second hypothesis reviewed on the cracked shaft with microphone array of four microphones. The symbols ◊, □, Δ, ⚙, x and o in Fig. 10 show the graph signals respectively at 500 rpm, 600 rpm, 700 rpm, 800 rpm, 900 rpm and 1000 rpm. The maximum amplitude value at 500 rpm shown in Fig. 10c with a value of 0.1, at 600 rpm the maximum amplitude shown in Fig. 10b with a value of 0.1194, at 700 rpm the maximum amplitude value illustrated in Fig. 10d with a value of 0.132. At 800 rpm is shown in Fig. 10b with a value of 0.1567, at 900 rpm shown in Fig. 10d with a value of 0.1577 and at 1000 rpm shown in Fig. 10a with a value of 0.221.

Linear regression equation in Fig. 11 is $y = 0.0001x + 0.0165$, meaning 0.0001 illustrates that every addition of one Hz will increase the amplitude value of 0.0001 mV. This known linear regression equation can be used to predict the amplitude value at various frequencies. Based on the previous results, it found that the amplitude value of the microphone array has a higher regeneration coefficient than the single sensor microphone signal and enhance the sensitivity of the microphone.

Mean square error: To know the parameter of quality of estimation signal to baseline signal then use Mean square error (MSE). The overall MSE value at the

cracked shaft with 500 rpm with the microphone array of two to four microphones shown in Table 3.

The result of the value of MSE, the lowest value is in the microphone array of four microphones. That is,

the more the number of microphones then the resulting estimation signal has a small MSE value. Small MSE values signify similarities with baseline signals.

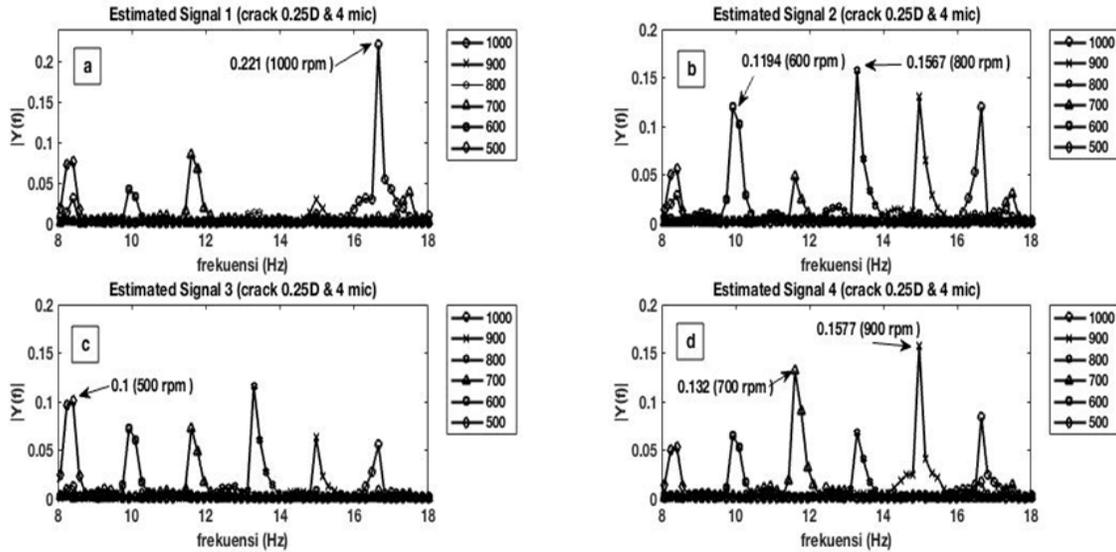


Fig. 10: Spectrum of estimated signal for four microphone at shaft speed 500-1000 rpm (8.33-16.67 Hz)

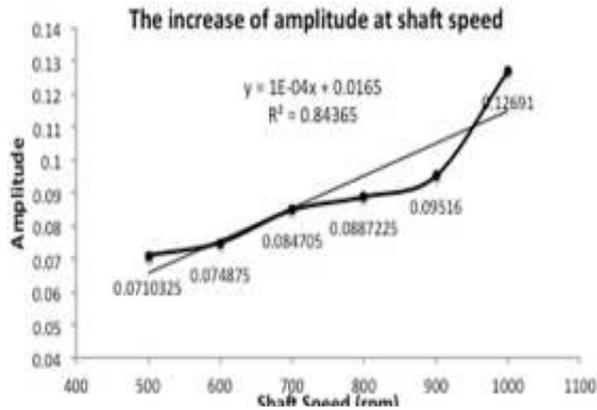


Fig. 11: The increase of amplitude at shaft speed variation

CONCLUSION

The test gives results indicating that increasing the number of microphones will increase the amplitude value as more microphones better capture the sound signal. The measured frequency of measurements with a single microphone and microphone array is very consistent and is at a frequency of 8,411 Hz, as shown in Table 2. The amplitude values in single microphone measurement are low. However, the amplitude value increases if the number of microphones increases while if the shaft speed increased then the amplitude value is also higher. The quality of amplitude parameters from baseline and microphone array measurements, it was found that the lowest MSE values were with four microphones.

The effect of using the number of microphones will be more detailed and well-tested if the microphone array modified with a nonlinear. Several other factors need to develop for future work, such as the rate of crack on rotating shaft, the depth of crack variation and noisy environment.

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