Underwater Acoustic Intensity Analysis using Noise Assisted-MEMD with Varying Distances

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Abstract— With current developments, underwater communication using acoustic signals is widely used. Many things need to be prepared to support a reliable underwater communication system, such as taking measurements in a test tank to find out the correct measurement configuration. Underwater acoustic intensity measurements, which are detailed in this paper, are performed in the test tank using distance variation schemes. Measurements were made at various distances of 4, 10, 20, and 50 meters from the signal source. The hydrophone that was used has a sensitivity of -180 dB re 1V/µPa. The hydrophone was placed at a depth of 2 meters below the surface of the water in the test tank, which divided the test tank depth in half to ensure that reflections from the bottom and the surface were kept to a minimum. However, the problem is that there are noisy signals at different frequencies. This paper proposes a method using Noise Assisted - Multivariate Empirical Mode Decomposition (NA-MEMD) to decompose the signal and then calculate the sound intensity. The result shows that an increase in the distance between the transmitter and receiver, also causes a change in the intensity with an average change of 0.467 dB/meter. It is concluded that the NA-MEMD approach was shown to be successful in decomposing the intended signal from the noise to equalize the quality of the signal received at different distances, and the correlation between intensity value and change in distance is resilient, with a correlation value of 0.98, indicating a very strong correlation.

Keywords— hydrophone; NA-MEMD; signal decomposition; sound intensity; underwater acoustic

I. Introduction

In shallow water condition, underwater acoustics signals contain noise that originated from different sources such as reflection of surfaces, interference from fish or acoustics signal generated by ships. These facts explain that there are many techniques develop to reduce noise such as deep learning approach [1], value decomposition algorithm [2], wavelet transform [3], or neural networks [4]. These techniques are chosen to cope challenges in applying underwater acoustics signal for communications such as frequency-dependent attenuation [5], short range of communication [6], and very low bandwidth [7]. In the application of underwater communication, the ideal signal is an acoustic signal. Acoustic signals can radiate up to a radius of several kilometres or over a long communication range. Underwater acoustic communication has been widely used by both the military and civilian sectors, such as in applications in tsunami response, coastal surveillance and monitoring, and inspection of oil and gas pipelines [8].

The acoustic signal suffers from a slight attenuation at low frequencies, and although it suffers increased attenuation at higher frequencies, it can travel longer distances than other alternative technologies. Signal attenuation is proportional to the distance and signal frequency used [9]. This principle is then applied to the test tank using instrumentation used to obtain the amount of signal attenuation on very low-frequency signals.

This paper will be discussed measuring underwater communication by sending an acoustic signal originating from the transmitter, which is then recorded by the receiver using a hydrophone at varying distances so that the value of the received sound intensity is known. Sound intensity (I) states the magnitude and direction of the acoustic field [9]. This measurement also needs to be done before starting measurements at sea. This aims to determine the ability of the instrumentation and the characteristics of the signals used in the measurement process.

However, in calculating the value of the acoustic signal intensity, there is a challenge, which is the presence of noise in the recorded signal. Therefore, it is necessary to do signal decomposition to obtain a signal with the desired frequency to calculate the intensity value. Empirical Mode Decomposition (EMD) is an adaptive method designed for multiscale decomposition and time-frequency analysis of nonlinear and nonstationary signal [10]. Using EMD, the original signal can be modelled as a linear combination of intrinsic mode functions (IMF) [11]. This method has proven to be quite powerful in various applications for extracting signals from data generated in nonlinear and non-stationary processes with certain noise, such as fault diagnosis in rotating machineries [12], wide range of biomedical signal analysis [13], oscillation detection in

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industrial processes [14], underwater acoustic target recognition [15], etc.

EMD is only designed for univariate data and is prone to mode mixing, which causes overlapping of signal spectra and aliasing of time-frequency information [11]. Based on the EMD algorithm, this method is then extended to decompose multi-channel signals known as multivariate empirical mode decomposition (MEMD). Unlike EMD, which only processes univariate signals, MEMD can decompose different channels simultaneously and establish common patterns among the channels, thus obtaining more accurate IMF estimates [11]. This advantage has been successfully applied to time-frequency analysis and classification of EEG data such as given in [16] and [17], and marine application given in [18], [19] and [20]. MEMD algorithm has the same base as EMD, so this algorithm is sensitive to noise and vulnerable to mode-mixing. To overcome the mode mixing problem, researchers have proposed various modified methods [21]. One of the most recent methods is Noise Assisted - MEMD (NA-MEMD) which exploits the quasi-dyadic filter bank property of MEMD on white noise [11]. Not only for processing multivariate signals, the NA-MEMD algorithm can also be used to process univariate signals with the help of noise and is proven to reduce the problem of mixing modes like EMD does, as well as provide a better time-frequency representation. These techniques have been applied successfully in geophysics [22], biochemistry [23], as well as complex dynamics process [24]. This paper is limited to filtering the noisy signal received in the hydrophone at a frequency of 5 kHz at various distances between the underwater speaker and the hydrophone.

In section II, research method is described based on steps given in several subsections i.e., preparation and measurement process, measurement results, filtering procedure as well as comparison and data analysis process. Section III contains results and discussion, and last section is closed with some conclusions.

II. Method

This section discusses proposed methods applied for the research. Steps taken are described as a flowchart, shows in Figure 1. Each step is explained in the following subsections.

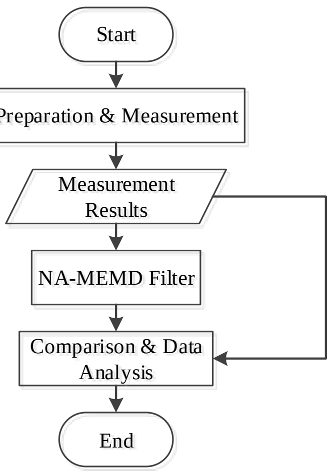


Figure 1. The flowchart of the proposed method

A. Preparation & Measurement

Instrumentations used in this measurement are divided into two different parts, i.e., as transmission and receiver part. As given in Figure 2 and Figure 3.

As shows in Figure 2, the reference signal is generated using MATLAB on a notebook that is attached to a sound-amplifier. The generated acoustics signal is broadcasted in the test tank using an underwater speaker DRS-8 that include its Audio Isolation Transformer of Oceanears.

On the receiver part, as shown in Figure 3, the H2a-XLR hydrophone serves to capture acoustic signals in the water. Using a soundcard connected to a notebook with ASIO driver for receiving system, these signals are recorded using data acquisition software.

Measurements were made in a test tank with a size of 200 x 11 meters and a depth of 5.5 meters. As illustration, the layout of the measurement setup in the test tank, can be seen in Figure 4. This test tank is usually used for a ship model test, where the experiments is conducted to get performances of ship designed. Due to this reason, the distances taken for this research is only limited to 4, 10, 20 and 50 meters. This distance is measured from the underwater speaker installation point, as the transmission part, to the hydrophone installation point, as the receiver part.

Figure 5 (a) shows how the hydrophone is hanging in the test tank. This hydrophone is mounted on a moving carriage of the test tank, so that the distance can be adjusted by moving the carriage. The hydrophone was placed at a depth of 2 meters below the surface of the water in the test tank. The depth of the test tank is divided in half by this measurement depth. This is done to ensure that reflections from the bottom and the surface are kept to a minimum. The measurement must be carried out in a state where there are no other sound sources that can interfere with the measurement results. Measurements were made with calm water conditions and no waves. On the other side, the underwater speaker is placed at a fix point and tied to the edge of the test tank. This setup can be seen in Figure 5 (b).

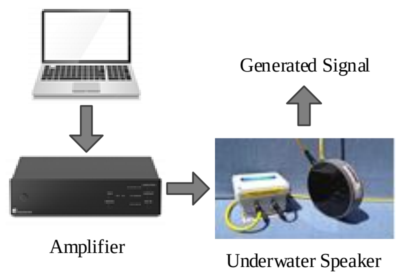


Figure 2. Instrumentation at transmission part

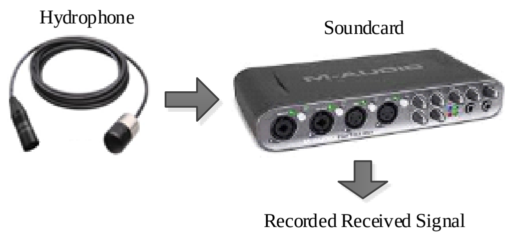


Figure 3. Instrumentation at receiver part

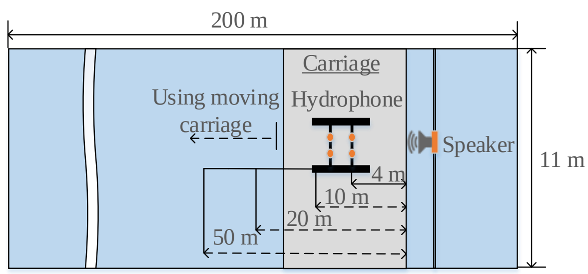
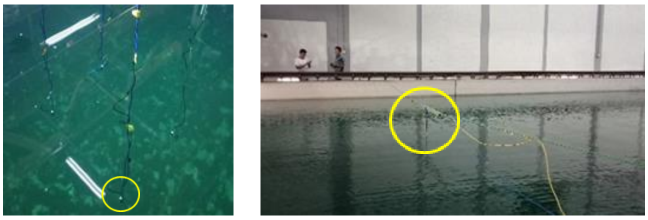


Figure 4. Configuration of instrumentation in the test tank



(a) (b)

Figure 5. Placement of hydrophones and underwater speakers in the test tank (a) hydrophone and (b) underwater speaker

B. Noise Assisted - Multivariate Empirical Mode Decomposition (NA-MEMD) Filter

Referring to Figure 1, the next step is NA-MEMD filtering stage. This method is an extension of EMD, which is applied to multivariate signals. Standard EMD decomposes a signal into a set of signal components with specific frequencies referred to as IMFs. Those IMFs represent the underlying temporal scale of the input data through an iterative process called a filtering algorithm [25]. The MEMD algorithm is used to process multivariate signals, which require several arbitrary channels. MEMD is explored by generating a multi-dimensional envelope, then taking projections of the signal along different directions, and finally averaging these projections to obtain a local mean [21]. In a position function, the algorithm used here, could be summarized as follows:

- Preparing the n-channels data as position function $x(X)$.
- Generating the set point based on the Hammersley sequence for sampling on an $(n-1)$-sphere.
- Computing a projection $p^{\theta_k}(x)\}_{x=1}^{X}$ of the input signal $\{v(x)\}_{x=1}^{X}$ along the direction of the vector y^{θ_k}, for all k acting $p^{\theta_k}(x)\}_{x=1}^{X}$ as the set of projections.
- Estimating the position points $\left\{x_i^{\theta_k}\right\}_{x=1}^{X}$ corresponding to the maxima of the set maxima of the projected signal $p^{\theta_k}(x)\}_{x=1}^{X}$.
- Interpolating $\left[x_i^{\theta_k}, v(x_i^{\theta_k})\right]$ for all values of k to determine the multivariate envelope curve $e^{\theta_k}(x)\}_{x=1}^{X}$.
- Computing the mean m(t) of the envelope curves for K direction vectors as $m(X) = \frac{1}{K}\sum_{k=1}^{K} e^{\theta_k}(x)$.
- Extracting the "detail" $x(X)$ using $d(X) = x(X) - m(X)$. If the detail satisfies the stoppage criterion for multivariate IMF, apply the above procedure to $x(X) - d(X)$, otherwise apply it to $d(X)$.

Despite its validity in processing multivariate non-stationary signals, MEMD inherits a degree of mode mixing [17], and therefore recently assisted MEMD (NA-MEMD) [11] was proposed by adding white noise as an additional channel. NA-MEMD explores the benefits of the MEMD quasi-dyadic filter bank structure on white noise and the realization of additional white noise that guarantees IMF reparability of the signal and noise channels. Given the n-channel input signal, the details of the NA-MEMD algorithm are described as follows [17]:

- Generate 3-channel noise using uncorrelated Gaussian white noise time series, which has the same length as the input. The generated Gaussian white noise has a multiplier factor of 2%, 3%, and 4% of the standard deviation of the input signal, respectively.
- Add the generated 3-channel (step 1) to the 1-channel input signal to obtain 4-channels of multivariate signals.
- Process the resulting 4-channel of multivariate signal using the MEMD algorithm to obtain multivariate IMFs.

From the resulting 4-variate IMFs, exclude the 3 channels corresponding to the noise, giving a set of 1-channel IMFs corresponding to the input signal.

C. Intensity Calculation

Intensity of the signal is calculated based on the principle of propagation of sound waves, which is related to the amount of emitted acoustic energy. This energy can be broken down into kinetic energy based on the motion of the particles and potential energy based on the resulting pressure force. The value of sound intensity is expressed in the following formula [26]:

$$I = \frac{p_0^2}{2\rho c} = \frac{p_{rms}^2}{\rho c} \tag{1}$$

The energy flux mean value, per unit of area and time, is the acoustic intensity *I*. It is equivalent to the average of the acoustic pressure and fluid velocity products. The water density is approximately $\rho_c = 997$ kg/m^3 on the average. Formula 1 is produced for a plane wave with amplitude p_0 and root mean square (RMS) value $p_{rms} = p_0/\sqrt{2}$. Sound intensity values can be denoted using the logarithmic notation in the form of decibels (dB).

D. Comparison and Data Analysis

As the final stage of the flowchart, the intensity of the signal after processing is compared to the intensity of the reference signal, generated in MATLAB. The reference signal is a sinusoidal signal with a frequency of 5 kHz. This paper is limited to discuss the signal with the frequency of 5 kHz. The data obtained from the acquisition has a format in the form of .wav. This data is then processed using MATLAB data processing software. In signal processing, there are several steps that need to be taken, as follows:

- 5 kHz sinusoidal signal segmentation.
- Signal decomposition uses the NA-MEMD method to separate the original signal from noise at a certain frequency.
- Analysis of sound intensity values.
- Convert the sound intensity scale with SI units into the dB scale.
- Examine the relationship between variations in intensity levels and variations in distance (*r*). The intensity is proportional to $1/r^2$ or can be explicitly written as follows [27]:

$$I = \frac{P}{4\pi r^2} \tag{2}$$

where *P* is the source power in watts.

III. Results and Discussion

The reason for achieving superior performance using NA-MEMD is to equalize the quality of the signal. After the signal is equalized, it is necessary to find out the correlation between intensity values and changes in distance. The intensity value is obtained from the calculation using MATLAB. Further details will be explained in the following analysis.

A. Intensity Value of Changes in Distance

The intensity value of the 5 kHz sinusoidal signal is obtained by analysing the digital signal and converting it into decibel (dB) units. In previous research, the same procedure was carried out at different distances of 1 meter, 5 meters, and 10 meters. Measurements from this previous research were accurate to within 10 meters. It is said that with greater distance, the signal intensity diminishes. The acoustic signal in water has an intensity that is roughly 4 times greater than that transmitted in air [28].

In this research, both the recorded signal decomposition and without it were used to calculate this intensity value. Without decomposition, the recorded signal still contains noise at certain frequencies. Table I shows the comparison of the 5 kHz sinusoidal signal intensity at each distance with and without NA-MEMD. The intensity value is obtained by calculating using MATLAB (1).

Without the NA-MEMD decomposition method, the average change value for sound intensity is 0.525 dB per meter. Aside from that, the NA-MEMD decomposition method generates the average change value of 0.467 dB per meter. The intensity value using NA-MEMD indicates the right value without any additional intensity from other undesired frequencies after the decomposition process.

The issue of aliasing between various source signals and background noise is satisfactorily resolved by NA-MEMD. The NA-MEMD approach is used with the purpose of equating the signal quality received at various distances. This method was also used, to decompose the multidimensional signal generated by the vibration of the roller bearing [29], estimate the rate of change of frequency [30], oscillation detector [31], and filter noisy seismic data [32]. In the previous research, the signals used were periodic signals, modulated signals, pulse signals, and chaotic signals with 10 Hz, 150 Hz, 152 Hz, and 10 Hz, respectively [29].

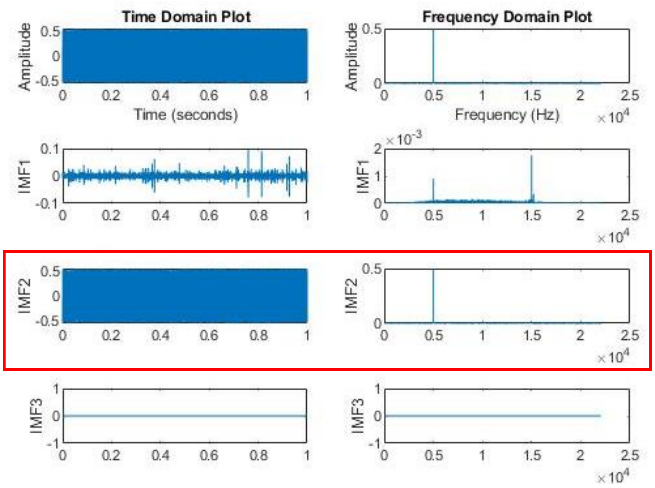


Figure 6. Decomposition of the received signal at 4 meters

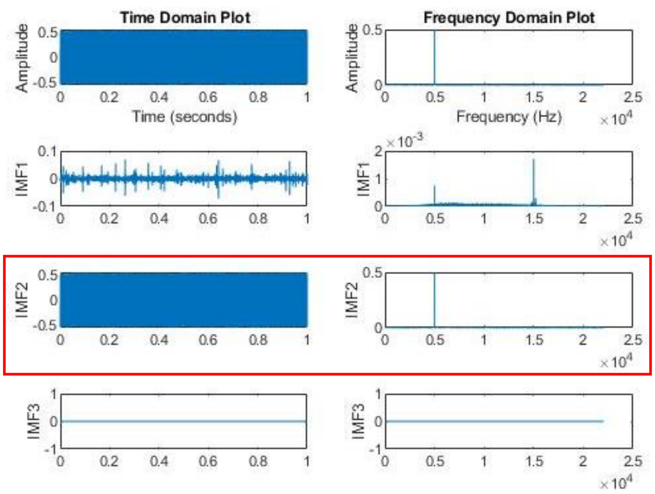


Figure 7. Decomposition of the received signal at 10 meters

TABLE I. INTENSITY VALUES COMPARISON OF SINUSOIDAL SIGNAL AT 5 KHZ

Distance (meter)	Intensity (dB)	
	Without NA-MEMD	**Using NA-MEMD**
4	52.60	49.73
10	49.38	46.70
20	44.32	41.15
50	34.76	30.85

From this research, the NA-MEMD approach was successful in breaking down multiple signals with frequencies of 15 kHz and 5 kHz, respectively, at the 4 and 10 meter distance variations indicated in Figures 6 and 7. As can be seen in Figures 8 and 9, the NA-MEMD is able to decompose signals with a wider range of frequencies, including 15 kHz, 5 kHz, and frequencies below 5 kHz, at distances of 20 and 50 meters. The decomposed signal is found in the results of the second IMF, which is marked with the red box. In general, Table I shows that noise increases the intensity of the source signal, which is about 3 dB, and this value is quite consistent across all signals with different distances. These results are certainly consistent with previous studies regarding intensity values before and after noise is removed [4]. With the variation in distance, the recorded signal attenuates as the distance between the transmitter and the receiver gets farther [9].

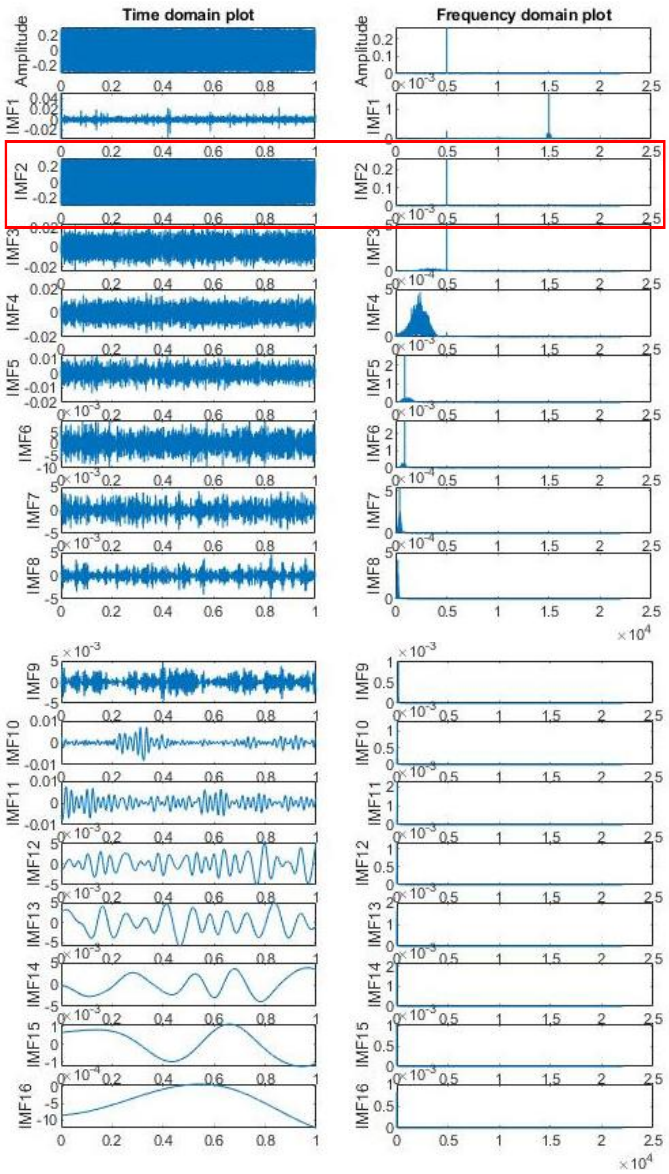


Figure 8. Decomposition of the received signal at 20 meters

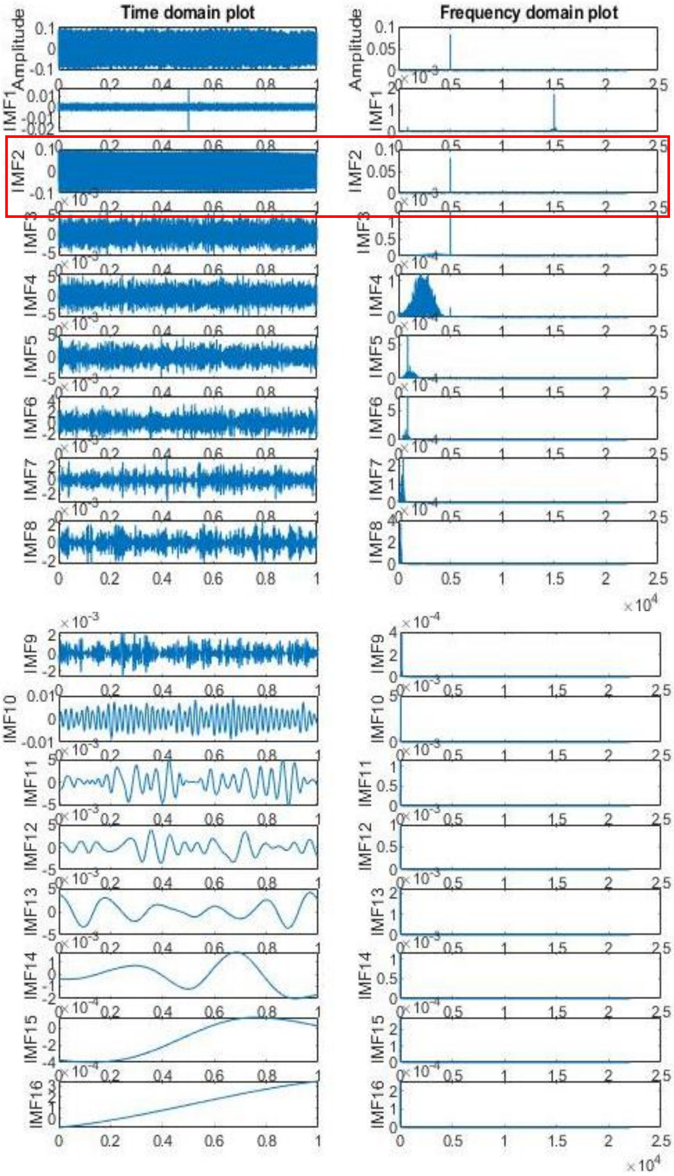


Figure 9. Decomposition of the received signal at 50 meters

B. Correlation of Intensity Values with Changes in Distance

The Pearson correlation test is a method that can be used to see how strong the relationship between two variables is, in this case, the relationship between changes in distance and sound intensity values. The Pearson correlation (r^2) has a range between 0 to 1. The closer the value is to 1, the stronger the relationship between the variables tested [33].

The relationship between changes in distance and sound intensity can be seen in Figure 10, where the value is 0.98, which means that the correlation between the two is very strong. However, this relationship is very strong because according to the basic theory, the acoustic emission curve decreases quadratically with increasing distance (2). Several factors affect this relationship, including the reflection of the signal from the surface and walls of the test tank, as well as the density gradient of the water due to the influence of gravity [34]. In accordance with the measurement results, the farther the distance between the transmitter and the receiver, the lower the value of the sound intensity that can be received by the receiver. Recent studies, [35] and [9] also show that there is a decrease in intensity as the distance between source and receiver increases.

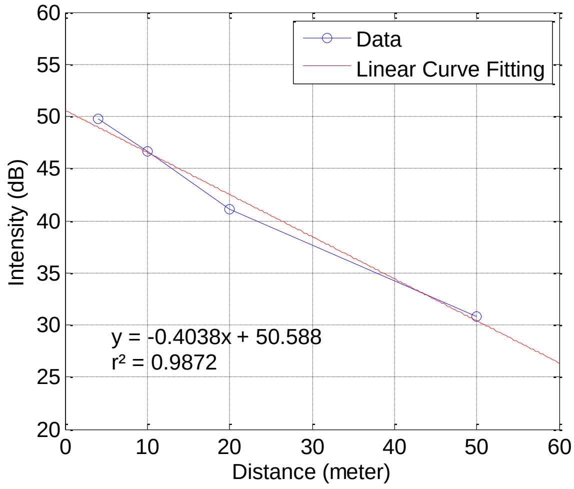


Figure 10. Correlation between intensity values with changes in distance

IV. Conclusion

This research attempts to solve the problem of calculating the sound intensity of a sinusoidal signal at a frequency of 5 kHz received by a hydrophone. The signal has noises, so it is necessary to separate the original signal from the noises itself. In calculating the sound intensity, the signal was previously decomposed using the NA-MEMD method. Signal decomposition using the NA-MEMD method has succeeded in separating the 5 kHz signal from the noise signals at certain frequencies. Without the NA-MEMD decomposition method, the average change value for sound intensity is 0.525 dB per meter, while using the NA-MEMD decomposition method generates an average change value of 0.467 dB per meter. The NA-MEMD method is effectively applied because when compared, the use of NA-MEMD can represent the intensity value without any additional intensity from other undesired frequencies after the decomposition process. From this research, it is concluded that the correlation between intensity value and the change in distance is robust, with a correlation value of 0.98. As a suggestion for further research, the NA-MEMD decomposition method can be applied by using a signal at a certain other frequency with more noises and a farther distance between the transmitter and receiver.

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