Application of Multivariate Empirical Mode Decomposition to Noise Reduction in Seismic Signal

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Abstract. The three-component signals of earthquake waves are very complex, requiring filtering methods that can filter three-component signal simultaneously. A good seismic signal is a signal that is free of noise, both in the instrument noise and in the field noise. In this paper, an effective and efficient filter method is proposed to reduce noise on the three-component seismic signal. The proposed method use multivariate empirical mode decomposition (MEMD) to decompose a multivariate signal into several intrinsic mode functions (IMF). MEMD is highly adaptive and can be very satisfying in time-frequency characteristics of signals. The method requires no prior knowledge of the target signals. MEMD method was tested on synthetic data with the different random noise level. The result shows that this method can reduce the seismogram of signal noise efficiently. This method is very effective to reduce noise, both on synthetic and field data.

Keywords: noise, earthquake data, adaptive filter, intrinsic mode functions, multivariate empirical mode decomposition

1. Introduction
The presence of high seismic activity in Indonesia will trigger a variety of natural disasters such as earthquakes and tsunamis. Therefore, mitigation efforts are needed to reduce the risk impact of earthquake and tsunami disaster. Mitigation of earthquake and tsunami disasters can be done by predicting the location and timing of the earthquake. To find out the location of the earthquake, the researcher should be able to analyze the hypocenter of the earthquake. Hypocenter analysis can be done easily if the seismogram is clean from noise. However, most of the earthquake signals are contaminated by noise, both instrument noise and noise from the propagation medium. This will make it difficult for researchers to analyze the arrival time of P and S waves. So we need a filtering method that can reduce noise in earthquake data.

Several methods of noise reduction in earthquake signals have been developed by some previous researchers [1–4]. Noise reduction in earthquake signals is very difficult because earthquake signals are very complex signals. The earthquake signals consist of three signal components, namely the North-South (N) components, the East-West (E) components and the Vertical (Z) components. The most common and often used method is the bandpass filter. Bandpass filter works by reducing noise at the high and low frequency. This method is able to reduce the noise in the earthquake signal, but can sometimes eliminate the information contained in the earthquake signals such as P and S waves. Until now, there is no method capable to reduce the noise very well.
Several adaptive filter methods have been developed to reduce noise on various signals. MEMD is one of a method that can reduce noise on various signals. MEMD has the ability to eliminate high and low-frequency noise from a signal without losing the guided information in the signal. With the ability of the MEMD method in reducing noise at various signals, it is possible that MEMD method to reduce noise on the seismic signal.

2. Methods

2.1. Empirical Mode Decomposition
Empirical Mode Decomposition (EMD) is a nonlinear and adaptive signal decomposition method. The EMD method does not make the assumption of linearity like the Fourier transform, and unlike the wavelet transform [5]. This feature offers a more successful decomposition especially for nonlinear and non-stationary data compared to Fourier and wavelet transforms [6]. A number of the intrinsic mode functions (IMF) and the residue functions are obtained from the signal data. The IMF covers local instantaneous frequencies, low-level IMF includes high local frequencies, and high-level IMF covers low local frequencies [6].

Here are the steps of the EMD method [7]:
1. All local extreme points (local maxima and minima) of the signal $x(k)$ are extracted.
2. Upper and lower envelopes are obtained by cubic spline interpolation of maximum and minimum points.
3. The mean envelope is calculated by the mean function of the upper and lower envelopes.
4. Let $h_1(k) = x(k) - m_1(k)$. 
5. If $h_1(k)$ is a zero-mean process, then the iteration stops and $h_1(k)$ is an IMF, named $c_1(k)$, else go to step (1).
6. Define $r(k) = x(k) - c_1(k)$.
7. If $r(k)$ still has least 2 extrema then go to step (1) else decomposition process is finished.

In the last procedure, we have a number of $n$ IMF, from $c_1(k)$ to $c_n(k)$ and a residue $r(k)$. The original signal can be represented as:

$$x(k) = \sum_{i=1}^{n} c_i(k) + r(k)$$

2.2. Multivariate Empirical Mode Decomposition
Mode mixing seems to be the most significant EMD weakness, which implies a single IMF consisting of very different scale signals or similar scale signals that appear on various IMF components and usually causes intermittency to analyze signals. Seismic data almost always contains some noise or random gap. If the decomposition is not sensitive to the additional noise of small but thin amplitude and has little quantitative and qualitative change, decomposition is generally considered stable and meets the physical uniqueness [8,9]. In general, EMD does not meet this requirement because decomposition is based solely on extreme distributions. To analyze more accurately the seismic signal, it is mandatory to eliminate mode mixing.

To overcome the lack of mode mixing problem present in the EMD, an intermittent test was proposed subjectively [10], but the effect is not anticipated. Then, Rehman and Mandic [11] proposed an Multivariate EMD (MEMD) to decompose a multivariate data (more than two input signals) simultaneously. This method is a new noise-assisted analysis method, to eliminate the mode mixing phenomenon and obtain the true time-frequency distribution of the original signal. The MEMD principle
is simple: adding white noise to the data, which distributes evenly across the entire frequency space, bit signals from different scales can be automatically designed to the exact reference scales set by white noise. The algorithm is very easy as described below [11]:

1. Generating the point set based on the Hammersly sequence for sampling on a \((n-1)\)-sphere.
2. Calculating a projection \(p^\theta_k \{t\}_{t=1}^T\) of the signal \(\{V(t)\}_{t=1}^T\) along vector direction \(X^\theta_k\), for all \(k\) giving \(p^\theta_k \{t\}_{t=1}^T\) as the set of projections.
3. Locating the time points \(\{t_k^0\}_{k=1}^K\) correponding to the maxima of the projected signal set \(p^\theta_k \{t\}_{t=1}^T\).
4. Interpolating \(\left[t_k^0, V(t_k^0)\right]\) all values of \(k\) to determine the multivariate envelope curves \(e^\theta_k \{t\}_{t=1}^T\).
5. For set of \(K\) direction vectors, the mean \(m(t)\) of the envelope curves is calculated as
   \[
   m(t) = \frac{1}{K} \sum_{k=1}^{K} e^\theta_k (t)
   \]
6. Extract \(d(t)\) using \(d(t) = x(t) - m(t)\). If the \(d(t)\) meets the termination criterion for multivariate IMF, apply the above procedure to \(x(t) - d(t)\), otherwise apply it to \(d(t)\)

2.3. Synthetic Seismogram
Prior to being applied to seismic signals, an MEMD method was tested on synthetic data as shown in Figure 1. Synthetic data in this paper is formed using the equation from Candra et al [12], as follows:

\[
 s_2 = \begin{cases} 
 0.2 \times \sin(300\pi t) & \text{when } 0.05 \leq t \leq 0.1 \\
 0.4 \times \sin(100\pi t) & \text{when } 0.15 \leq t \leq 0.25 \\
 0 & \text{other}
\end{cases}
\]

(2)

The use of synthetic data makes it possible to validate the accuracy of the methods used. If good results are obtained, it can be continued by analyzing the actual seismic signals. the proposed method is tested to determine the stability of dealing with noise by adding noise levels of 10\%, 15\% and 25\% using the following equation:

\[
 S_{\text{cont}}(t_i) = S(t_i) + k \left( \text{randn}(i) \right) S(t_i)
\]

(3)

Where \(S_{\text{cont}}(t_i)\) is the noise contaminated seismic signal, \(S(t_i)\) is seismic signal \(k\) is the noise level and \(\text{randn}(i)\) is random normal number which range is (0, 1). The random normal number interval does not include the extreme value, 0 and 1. The result of the noise-contaminated seismic signal is shown in Figure 2.
3. Result and Discussion

3.1. Synthetic Data

Candar et al [12] generate Synthetic data of seismic signal using the sinusoidal signal by adding noise 10%, 15%, and 25% respectively. The example of synthetic data with the various noise are shown in Figure 2. The purpose of adding random noise is to generate data that is very close to the real field data.

The noise reduction process of non-linear and non-stationary signals is done by dividing data into small panels to obtain a linear event called IMF (Intrinsic Mode Function). MEMD decomposes seismic signals into a number of intrinsically oscillating components or called Intrinsic Mode Functions (IMF). Each component on the IMF has different frequencies. This decomposition has the assumption that any data consists of various models of intrinsic oscillation. Any intrinsic mode (linear or non-linear) is an...
oscillation that will have the same extreme amount be symmetric to the local average [8]. The example of decomposes seismic signal using MEMD to obtain the Intrinsic Mode Functions (IMF) is shown in Figure 3. To obtain the good result of the seismic signal, we must identification where is the good IMF and eliminate the noise and residual. After identifying a good IMF, then the next step is to restructure the selected IMF as shown in Figure 4. The result of MEMD analysis of 10%, 15%, and 25% noise is shown in Table 1.

**Figure 3.** Example of MEMD analysis of synthetic seismic signal with 25% noise added.

**Figure 4.** The curve fitting of the MEMD analysis result of synthetic seismogram with 25% noise after IMF selection.
Table 1. Error Calculation of the Synthetic Data

| Noise Level | 10% | 15% | 25% |
|-------------|-----|-----|-----|
| EMD [12]    | 1.38| 1.73| 1.87|
| EEMD[12]    | 0.56| 0.59| 0.77|
| MEMD Result | 0.54| 0.58| 0.59|

According to the Table 1, the error calculation of the MEMD analysis is approximately 0.57%. The error percentage value is less than the random noise level. Similarly, curve fitting result of the synthetic data shows very good results for each noise addition. Based on the result, the error percentage value of MEMD method is less than the previous method (EMD & EEMD). This is shows that the MEMD method is very effective to reduce noise on the seismic signal.

3.2. Field Data

MEMD method is applied in the real seismic signal to validate the applicability. The seismic signal obtained from earthquake occur in West Sumatra on October 25, 2010, with magnitude 6.3 Mw recoded by BLSI (Bandar Lampung) station (BMKG IA network) is shown in Figure 5. We can see that the three-component seismic signal is contaminated with noise. Then the MEMD method is applied to reduce the noise from the seismic signal. Based on the result of MEMD analysis, this method is an accurate and efficient method to reduce the noise of seismic signal. As we can see in Figure 6, we can easily determine the P and S waves from the noise-free seismic signal.

![Figure 5](image)

Figure 5. The Seismic signal of October 25, 2010, Mentawai earthquake recorded by BLSI station.
Figure 6. The MEMD analysis result on the seismic signal that generates a noise-free seismic signal.

4. Conclusion
The proposed MEMD method in this paper is able to construct seismic signals that are free from noise. This method is developed based on the concept of signal decomposition to decompose the original signal from the existing noise. The MEMD method is tested for validity using synthetic data with the addition of various random noise. The result of noise reduction on three-component earthquake signals indicates that the MEMD method can reduce noise very well. The MEMD method works very well to reduce noise, both in synthetic data and field sample data. The results showed that MEMD methods better than EMD and EEMD method. The advantage of the MEMD method is that no prior knowledge of the target signal is required. Furthermore, the MEMD method can filter out noise from three-component seismic signals simultaneously so that the information from the noisy contaminated signal will not be lost. Therefore, the MEMD method can be recommended as a filter tool for determining P and S waves in seismogram analysis.

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