Time Frequency Signal Classification Using Continuous Wavelet Transformation

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Abstract. Time-frequency analysis can provide useful information in digital signal seismic data processing and interpretation. The energy concentration of the spectrum depends on the consistency of function of the time-frequency analysis and instantaneous frequency variation digital signal. In this case, we used the digital signal seismic from selected seismometer broadband which deployed in Sumatera Island. The aim of this study to classify the waveform based on the time-frequency analysis using continuous wavelet transform (CWT). The sample data used the earthquake of 20 February 2018 in North Sumatera. The result indicated the classification between the horizontal and vertical components from the seismometer broadband is different. The classification of vertical is affected by seismic source and horizontal component affected the site effect.

1. Introduction

Time-frequency analysis can reveal useful information in the digital seismic data. The high resolution of the time-frequency representation is of great importance to characteristic the signals. Digital signal seismic or earthquake wave characterization is essential for better understanding wave and local site effect subject of the earthquake [1], [2]. Earthquake activity in Indonesia is potential and will be interested in the study. The location of Indonesia in the ring of fire-making earthquake activity and disaster will be happening every time. Based on these situations, Indonesia deployed more seismometer broadband to monitoring and analysis of the earthquake. Earthquake waves can record from seismometer broadband in digital signals in SEED data [3]–[5]. In seismic design, the waveform of seismometer broadband consists of horizontal (East and North) and vertical (Z) component [6]. The vertical component of input ground motion has been taken into account and an important role to be considered, regarding the seismic response of the critical structure. In this case, we used the waveform which recorded from selected seismometer broadband in the Sumatra earthquake in 2018, 20 February. The waveform had been recorded form any sensor not only close to the event but also sensor from other
fields. The characteristic of the digital signal is very important to evaluate the performance of the sensor. To evaluate each sensor which recoded in this case, we can use time-frequency analysis to classify the vertical and horizontal component. The time-frequency is an important technology in digital signal seismic processing. Time-frequency analysis computed using CWT. The CWT has played a key role in time-frequency information in many fields of digital signal processing.

The main problem of the digital signal seismic is how to classify the waveform based on the vertical and horizontal component as affected by the seismic source and site effect. This study aim to classification and identification of the time-frequency based on the vertical and horizontal component.

2. Data and Methods
2.1 Data

The digital signal seismic data were employed from the BMKG-IA network. We use the Sumatra earthquake in origin time 2018-02-20 T 23:40:49, Mag. 4.8 in lat. 1.03, long. 98.69 and depth 80.0 Km in Northern Sumatra, Indonesia. We select the station of seismometer broadband in Table 1.

| No | Code | Network | Lat (N) | Long (E) | Stream       |
|----|------|---------|---------|----------|--------------|
| 1  | BKNI | IA      | 0.33    | 101.04   | BHE, BHN, BHZ |
| 2  | GSI  | IA      | 1.30    | 97.58    | BHE, BHN, BHZ |
| 3  | KCSI | IA      | 3.52    | 97.77    | BHE, BHN, BHZ |
| 4  | MNSI | IA      | 0.80    | 99.58    | BHE, BHN, BHZ |
| 5  | PBSI | IA      | -0.05   | 98.28    | BHE, BHN, BHZ |
| 6  | SNSI | IA      | 2.41    | 96.33    | BHE, BHN, BHZ |
| 7  | TDNI | IA      | 0.57    | 97.82    | BHE, BHN, BHZ |
The distribution of selected seismometer broadband and earthquake location shown in Figure 1. In this study, we selected the sensor which deployed in Sumatera Island, we selected sensor based on the location of the earthquake to the seismometer broadband.

3. Methods
The methods of this study using Continuous Wavelet Transform, CWT is descending cross-correlation between a signal $s(t)$ and family of wavelets as shown in Eq.1

$$W_s(a, b) = \frac{1}{\sqrt{a}} \int s(t) \Psi^* \left(\frac{t-b}{a}\right) dt$$

where $a$ and $b$ are scales and time shifts of a indication wavelet $\Psi$, respectively, $\Psi^*$ is the complex conjugate of the reference wavelet, $t$ is time and $W_s(a, b)$ is the time-scale representation of the signal [7]–[11].

The temporal length of the wavelets used in the cross-correlation is varied differing on the frequency component under investigation. The effective and operative at identifying a feature in digital seismic data as combining the machine learning wavelet-based. In this study, we use the mlyp as phyton open-source machine learning library built on NumPy/SciPy and GNU Scientific Libraries. Mlpy provides a wide range of state of the art machine learning methods [12], [13] such as Multi layer Perceptron or Deep Learning [14].
The general methods of this study show in Figure 2, the methods of Time-Frequency classification starting from converting the row data MSEED to the vertical and horizontal component. Time-Frequency analysis computed by CWT and using package machine learning python (mlpy). The CWT for time-frequency analysis produced a high resolution in time and frequency in spectral.
4. Result and Discussion

The result of the analysis of the time-frequency of the selected sensor in this study can show in Figure 3. The classification of time-frequency based on CWT had been present, the computation of CWT is an accurate efficacious and efficient method to improve the quality of the digital earthquake signal. Classification of a digital signal earthquake in this study had been a matter of extensive research.
The Time-Frequency classification based on CWT had been plotted in Figure 3. The classification of digital signals computed for the vertical and horizontal components. The different time-frequency representation is presented in Figure 3. The CWT representation is calculated using a morlet wavelet. We select seven sensor stations close to the earthquake location. Figure 3 (a-c) is spectral of the BKNI sensor in the time-frequency. The waveform of the signal on the top indicates the observation seismic record of an earthquake. The computation of BKNI for vertical (BHZ) and horizontal (BHE, BHN) component is clear to detect the event in the P phase and S phase. The result of the BKNI sensor shows the frequency energy. Figure 3 (d-f) is the time-frequency spectral of the GSI sensor form record event location. Both of the GSI station in Figure 3 (d-f), KCSI station in Figure 3 (g-i), PBSI station in Figure 3 (m-o) and SNSI station in Figure 3 (p-r) is clear to detect the earthquake waveform in this study. The classification of time-frequency shows the P phase, S phase, and energy. Different time-frequency spectrogram like a representation of MNSI in Figure 3 (j-l) and TDNI in Figure 3 (x-z). The result of the MNSI station shows the sensor not recorded the event and had seismic noise. The TDNI station shows not detected the waveform of earthquake activity, the time-frequency classify can be not described P phase and S phase. The classification of vertical component is affected by the seismic source and the horizontal component is affected by the site effect.
5. Conclusions
In this study, we present the time-frequency classification using CWT. Based on the result, the variable time-frequency resolution of the CWT enables analysis of a truly vertical and horizontal component of broadband digital signals. The characteristic of vertical and horizontal components shows the phase difference is likely to show a simple relationship when it plotted in frequency. The phase difference becomes constant in terms of the horizontal and vertical components in the lower frequency range. The classification of time-frequency using CWT has designed an information confidence measure of time-frequency and multi-scale.

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