INNOVATIVE SEISMIC PHASE DETECTION THROGH HILBERT-HUANG TRANSFORM

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Surface waves convey great deal of information by themselves and seismologists and engineers appreciably have been seeking reliable methods to exclude them among other phases. But parts of restrictions (e.g. presence of white noise and/or coda waves with non-Gaussian distribution belonging to body-waves and non-stationary seismic signals makes this aim as an extremely demanding and delicate task. To this end, different approaches have been examined so far. These discriminations are historically based on different characteristics, attributed to each individual phase, that provide a criterion to single out desired phases. Basically, classic algorithms, e.g. STA/LTA, Stewart (1977), autoregressive AIC phase picking algorithm, polarization analysis (Flinn (1965); Kanasewich (1981); Jurkevics (1988); Vidale (1986), Jackson *et al.* (1991)) progressively paved the way to automate and accurate this purpose. Fundamentally, natural time series are of non-stationary and non-linear signals. Furthermore, their dependency to signal's frequency content, and their transient nature together with overlapping coincidence, occuring for different phases, undermine applicability of traditional approches. Particularly, Fourier transforms and short window Fourier transforms are unable to extract transient phenomena effectively and this deficiency stems mostly from its corresponding Complex Exponential Functions which employed for decomposing in frequency domain. This kernles are decentralized in both time and frequency domain and regarding this drawback, seismologist are in need of an alternative approach to circumvent these restrictions. Accordingly, researchers were bridged time and frequency domains together to bypass these imposed deficiencies. To this end, Baranov (2010) enhanced the results of STA/LTA method with joining it with Discrete Wavelet Decomposition. Pinnegar (2006) used S transform, and analogously Anant K, et al (1997), L. D'Auria, et al (2010), Galiana-Merino JJ, et al (2011), and Ramirez J and Meyer F (2011) implemented Discrete Wavelet Transform to extract desirable phases. Following Lockman and Allen (2005), Hildyard, et al., (2008) utilized Predominate Period as a detector. Using complex seismic trace analysis (Taner et .al (1979), Morozov and Smithson, (1996)) introduced as an operable method for deriving non-overlapped phases. Some researchers attempted to combine all possible features through a decision operator (e.g. Bai & Kennet, (2000), Diehl T et al., (2009)) through well-known supervised classification (e.g. by Kernel support vector motion or Neural Network methods) or unsupervised clustering algorithm (e.g. Kohler et al, (2009) who collected a complete sets of seismic attributes and exploited them for unsupervised phase detection through Self- Organizing Maps). Diallo et al. (2006), Diallo et al. (2007), Kulesh, et al. (2007) addressed applicability of Continuous Wavelet transform method for adaptive polarity filtering of generated surface waves.

Wigner-Ville distribution, Wavelet transform and other advanced Quadratic Time-Frequency Analysis (Cohen's Class) are unable to meet non-linearity of signals (e.g., Huang et al. (1998)), so recently great efforts devoted to contrive a method satisfying both non-linearity and non-stationary

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characteristics coincidently. Hilbert-Huang transform provides a step-forwarding trend. This approach integrates Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis in the unitary framework, disseminated within engineering and seismological applications, as an appropriate alternative of regular tactics. Zhang R et al (2008) employed EMD Decomposition as a robust way for identification of temporary phases and their features (e.g. instantaneous frequency). EMD supplements a robust way to treat these local variations and divides time series into several intrinsic oscillating mode functions (imf) conveying parts of entire signal's information. We can demonstrate that average frequency of a real signal $s(t)$ is

$$\langle \omega \rangle = \int \left(\varphi' - \mathrm{i}\frac{a'(\mathrm{t})}{a(\mathrm{t})} \right) a^2(\mathrm{t}) dt \tag{1}$$

Where $a(\mathrm{t})$ is $(s^2(\mathrm{t}) + y^2(\mathrm{t}))^{1/2}$ and $\varphi(\mathrm{t})$, indicated instantaneous frequency, is $\arctan\left(y(\mathrm{t})/s(\mathrm{t})\right)$. In this definition $y(\mathrm{t})$ is Hilbert transform of $s(\mathrm{t})$. We implicitly supposed a and φ vary smoothly but this assumption is not the case for earthquake's time series (e.g. Huang et al. (2003), Zhang (2003)). To overcome this contradiction we could decompose signals into the finite set of intrinsic mode functions (IMF) enabling us to extract meaningful insight for their Hilbert transforms.

Now we could declare each one of IMFs will have a close resemblance with a simple harmonics, so this indicates we can confidently insert them into the Fourier transform. Physically, to meet required conditions for having a meaningful instantaneous frequency, functions should be symmetric respect to the local zero mean and have the same number of zero crossings and extrema. An intrinsic mode function (IMF) is defined as a function that satisfies two conditions: (1) the number of extrema and the number of zero crossings must either equal or differ at most by one in the whole data set, and (2) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero everywhere. A systematic way to extract the IMFs, designated as a sifting process, is based on the following assumptions: (1) the signal has at least two extrema, and (2) the characteristic time scale is defined by the time lapse between the extrema. For a sample data, recorded following a shallow depth Ms=6.4 Earthquake in Gilan station, located in 120 km epicentral distance. The sifting process is depicted through an illustrating flowchart in Fig. 1(a) and its extracted IMFs are also shown in Fig. 1(b). Once we have these intrinsic mode functions for desired rotated components, Hilbert transform can be applied to each component to get the amplitudes and the instantaneous frequency.
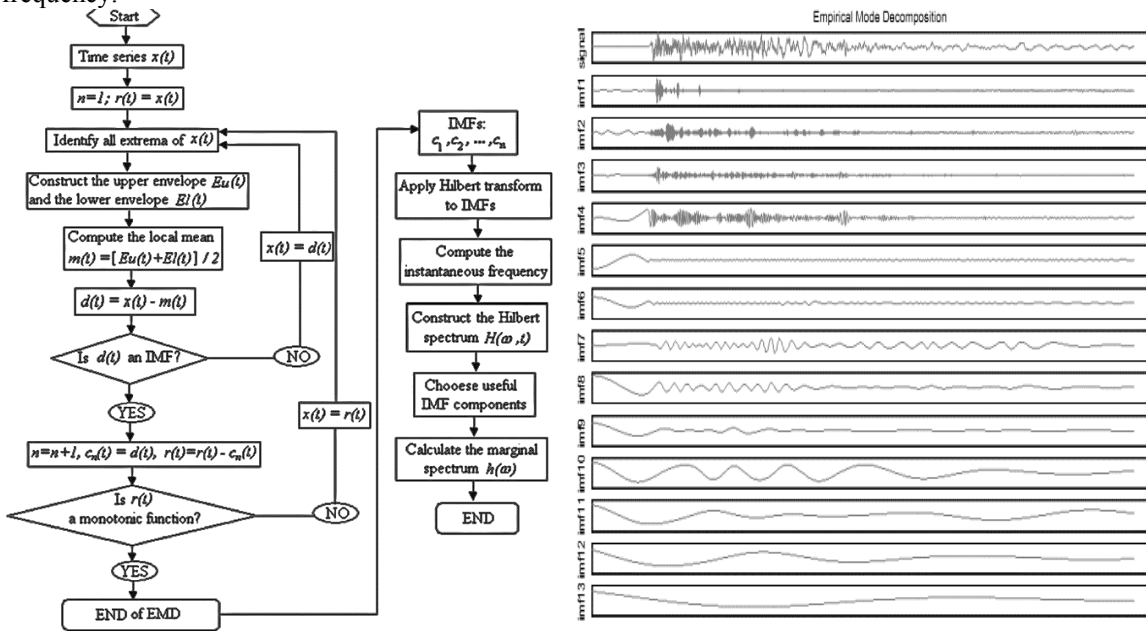

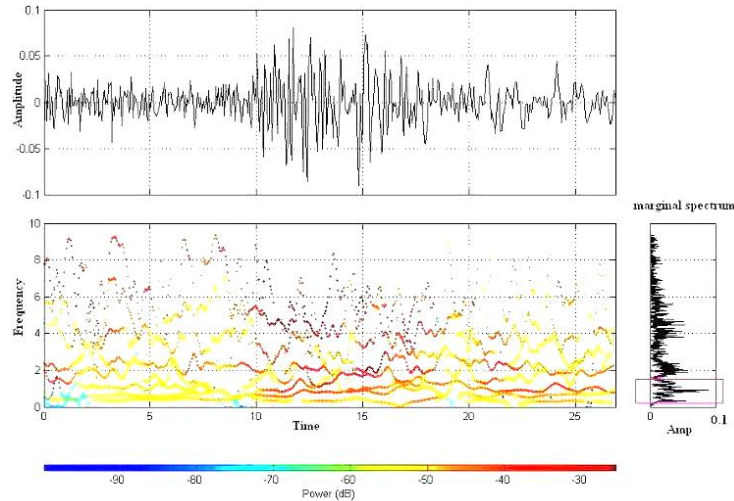Figure 1. (Left) EMD Algorithm (Right) Decomposed IMFs up to 13 Level.

Figure 2. Time-Frequency representation for top signal. (Right) Marginal Spectrum.

Time-frequency distribution of the amplitude is designated as the Hilbert spectrum $H(\omega, t)$, and $a_j(t)s$ are also a time-dependent expansion coefficient. $\omega_j(t)s$ are the instantaneous frequencies. Therefore,

$$\mathrm{x}(t) = \Re \sum_{i=1}^{n} a_j(\mathrm{t}) \exp(\mathrm{i} \int \omega_j(\tau) \, \mathrm{d}\, \tau) \qquad (2)$$

Where $\Re$ stands for the real part of the complex number. As a result, the marginal Hilbert spectrum and the instantaneous energy are $h(\omega) = \int_0^T H(\omega, \mathrm{t}) \, \mathrm{d}\, t$ and $IE(t) = \int_\omega H(\omega, \mathrm{t}) \, \mathrm{d}\, \omega$, respectively. With the extension of an adaptive criterion, utilized $h(\omega)$ and $IE(t)$, to the Hilbert-Huang domain, we constructed different filtering algorithms to separate Rg surface waves respect to the different magnitude ranges, distance offsets and depths. We examined efficiency of this method for both shallow depth earthquakes and explosions (for instance one of them was shown in Fig. 2 and correspondingly, its separated Rg phase was also represented in Fig. 3).
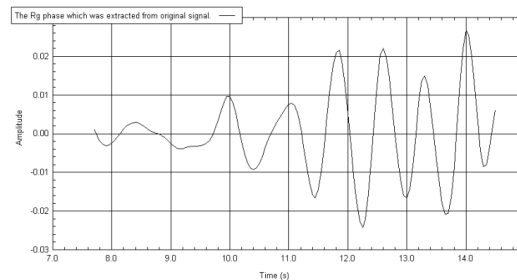

Figure 3. Ultimate extraction of Rg phase.

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