Lateral consistency preserved Variational Mode Decomposition (VMD)

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Summary

Seismic decomposition discriminates different geological expressions by isolating seismic signals of particular frequency ranges. As a novel signal decomposition method, Variational mode decomposition (VMD) exhibits advanced features compared with the classic Empirical Mode Decomposition (EMD) method. VMD can resolve the instinct mode functions (IMFs) more robust and reasonably. Besides a synthetic example, we show a field application of the VMD in sedimentary cycle identification. However, like other high resolution decomposition method, traditional VMD also decomposes data trace by trace, which would result in poor lateral consistency. In order to appropriately apply it on seismic data, a lateral consistency preserved VMD method is proposed to meet the challenges of seismic application, which has been verified through field applications to be valuable for further analyses.

Introduction

Seismic decomposition shows people more hidden information in the data than superficially. As the most classic spectral analysis tool, Fourier transform gives us the stationary frequency information. But, seismic signal frequency changes along the traces and depth, termed non-stationary and need to be analyzed with time frequency analysis (TFA) methods (Han & van der Baan 2013). Developing from Fourier transform, short-time Fourier transform (STFT) and continuous wavelet transform (CWT) are classical TFA tools (Partyka et al., 1999; Sinha et al., 2005), but this kind linear convolution based methods are bound by the Heisenberg uncertainty principle with a tradeoff between time and frequency resolutions (Tary et al. 2014). The highest vertical resolution is achieved by a method based on a matching pursuit (MP) approach, whereby the waveforms in a mother wavelet library are matched to a seismic trace in an iterative process according to the highest spectral energy (Wang, 2007). But the performances of MP methods depend on the configuration of wavelet library and fitting methods, while it also occasionally fails to consistently match wavelets to the relatively low energies at the low/ high frequencies.

As a data-driven signal decomposition method, Empirical mode decomposition (EMD) (Huang et al., 1998) analyzes non-stationary signal and has been widely used (Klplan et al., 2009). But instinct mode function (IMF) of EMD is not based on bandlimited assumption, so EMD attacks all energy at high wave-number. Regarding to this drawback, variational mode decomposition (VMD) (Dragomiretskiy and Zosso, 2014) was proposed for decomposing a data into an ensemble of band-limited IMFs.

In this paper, we first introduce the principles of EMD and VMD. Then in order to apply VMD on seismic processing/interpretation, we propose a lateral consistency preserved VMD method. In the artificial signal decomposition example, we compare EMD and VMD to illustrate their differences. Next, based on a sedimentary model test, we investigate VMD's capability in sedimentary pattern recognition. Later, a field application shows through the division of sedimentary cycle, we can get the stratigraphic sequence framework to guide the reservoir prediction. After displaying the 1D case, we show the proposed VMD results on vertical sections compared with the traditional 1D VMD, which confirms the lateral consistency reinforcement is necessary and effective.

EMD

EMD decomposes a data series into a finite set of IMFs, which represent different oscillations embedded in the data. They are constructed to satisfy two conditions: (1) the number of extrema and the number of zero-crossing must be equal to or differ at most by one; and (2) at any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero. Each IMF has a localised frequency content by preventing frequency spreading due to asymmetric waveforms. The IMFs are elementary amplitude/frequency modulated harmonics that can model the nonstationarity and the nonlinearity of the data (Huang et al., 1998).

Lateral Consistency Preserved VMD

VMD decomposes a real input signal into a number of modes that have specific sparsity properties while reproducing the input. Meanwhile, the sparsity prior of each mode is chosen to be its bandwidth in spectral domain. The IMFs are extracted concurrently instead of recursively, leading to its high effciency. VMD is achieved by solving the following optimization problem:

$$\min_{\{u_k,\ \omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} * u_k(t) \right) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$
$$s.\ t. \quad \sum_k u_k = f \qquad , \qquad (1)$$

where u_k and ω_k are modes and their center frequencies, respectively. The summation over all modes is input signal.

The goal of VMD is to decompose an input signal into a discrete number of sub-signals (modes) that have specific sparsity properties while reproducing the input. We assume each mode to be mostly compact around a certain "oscillation", which is to be determined along with the decomposition. However, if all modes are determined only from the current trace, the lateral consistency is hard to be assured, which is of great importance in seismic processing and interpretation. Thus, we modify from only using single trace to employing the surrounding traces, which means we use the trimmed medium "modes" of a local small area instead of just a single trace. (The field seismic example in Figures 6 and 7 demonstrates the differences between traditional and proposed VMD methods.)

Artificial Signal Decomposition

In order to compare EMD and VMD, we design a mixed signal with a lower background frequency and a gapped higher frequency. The analyzed signal is $s = s_1 + s_2$ with

$$s_1 = \sin\left[2\pi * 0.055 * (t-1)\right] \quad if \quad 1 \le n \le 500$$
$$s_2 = \begin{cases} \sin\left[2\pi * 0.69 * (t-1)\right] & if \quad 101 \le n \le 350 \\ 0 & else \end{cases}, \qquad (2)$$

Figure 1 and 2 show IMFs from EMD and VMD. The two components can be clearly resolved by VMD and separated signals are basically consistent with the original ones.

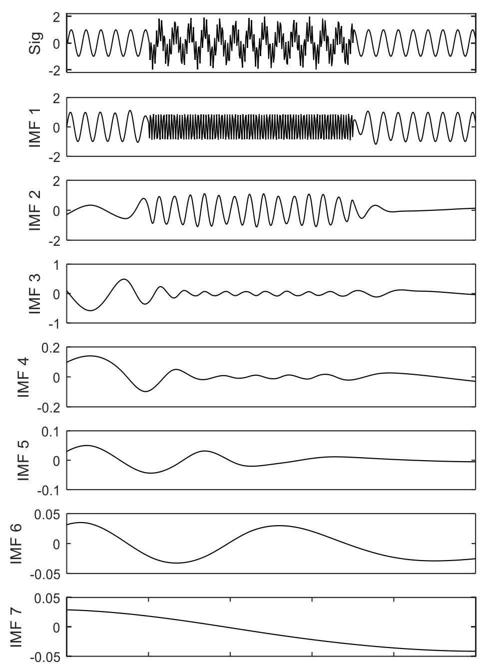

Figure 1: Decomposition of the artificially mixed signal by EMD.

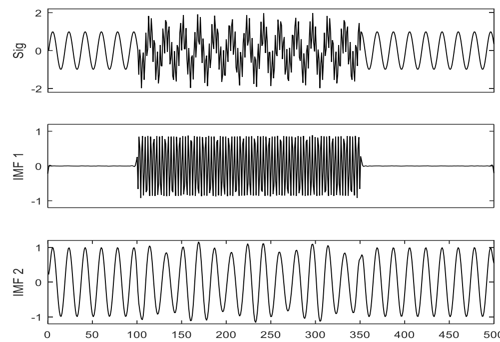

Figure 2: Decomposition of the artificially mixed signal by VMD.

While EMD can decompose the signal, it generates seven different IMFs, which is hard to be used in signal analysis. So we believe that VMD method can decompose seismic signal without generating too many IMFs.

Sedimentary Pattern Identification

Sedimentary cycle is the result of the periodic occurrence of any depositional event. It is mainly caused by the earth's crust periodic oscillation (Liu et al., 2015). The key for division of the stratigraphic sequence is dividing the sedimentary cycle correctly, which can be done by processing the logging data. But, well logs cannot cover the whole survey. So, we want to extract the sedimentary cycle from the seismic using a signal decomposition method, which should be data-driven and robust. From the previous introduction and example, VMD becomes our choice.

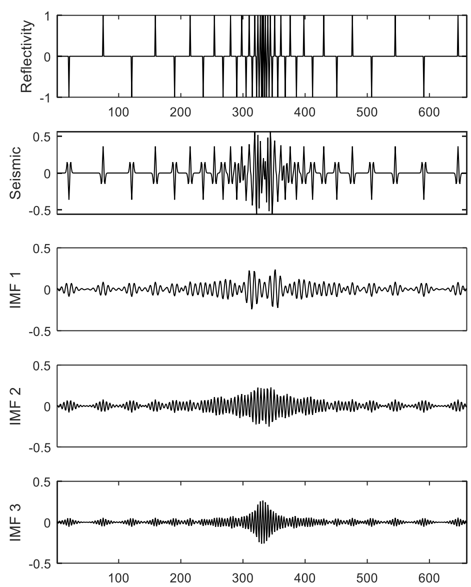

Figure 3: Normal-inverse cycle model test: reflectivity series, seismic and IMFs from VMD.

There are four kinds of typical cycle model: a) Normal, b) Inverse, c) Inverse-normal, and d) Normal-inverse cycle model. As the above four models are similar to each other, we only build the last one, Normal-inverse cycle model, which means grain size change from fine to coarse then from coarse to fine with energy and frequency first increases then decreases. The reflectivity series, seismic are shown in Figure 3. VMD is used to decompose the seismic signal. Note the sedimentary changes are clear on IMF3 compared to the reflectivity.

Field Application

The field data set is from the Fort Worth Basin, Texas. The Barnett Shale reservoir falls between the Marble Falls and Viola Limestones which form the frac barriers (Perez and Marfurt, 2014). A thin Forestburg Limestone which can acts as an imperfect frac barrier separates the reservoir into the Upper Barnett and the Lower Barnett sections. Figure 3 shows the seismic data and inverted seismic impedance with the interpreted Marble falls, Upper Barnett shale, Forestburg, and Lower Barnett Shale. As our objective is to analyse the sedimentary cycle, we choose Marble falls limestone to be the target area.

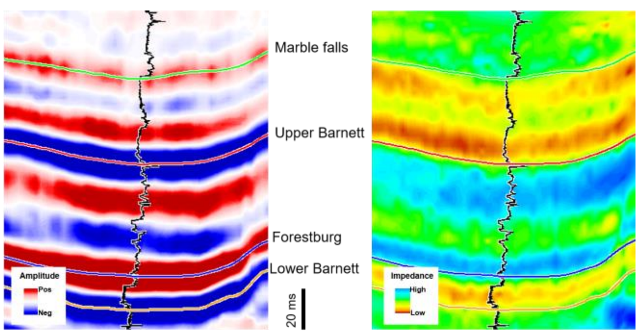

Figure 4: Field application. (Left) Seismic profile. (Right) Inverted seismic impedance.

Figure 4 shows the vertical seismic section and impedance with horizons annotated. It is hard to find the sedimentary cycle directly from seismic. Figure 5 shows the IMFs from VMD of the Marble falls Limestone. The seismic trace is extracted from 10 ms above Marble falls horizon and 10 ms below Upper Barnett shale horizon. So it is about 60 ms long. From the IMF1, we can clearly see a Normal-inverse model pattern, shown in Figure 3. From the gamma logs in Figure 4, we can also see a similar curve in the middle of Marble falls. So, this application persuades us that VMD like signal decomposition methods can be used in sedimentary pattern characterization.

After examining the seismic trace passing through the well location, we apply the VMD method on the whole seismic volume. Spectral decomposition methods can produce multi spectral components to highlight certain scale geological structures (Li and Lu, 2014). So, we expect IMF volumes from VMD can also reveal some geological information.

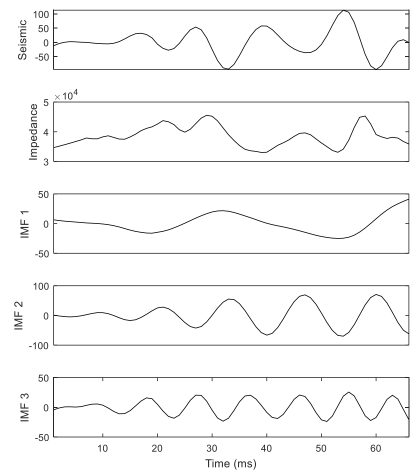

Figure 5: Seismic decomposition from VMD of Marble falls Limestone.

Figure 6 displays vertical seismic section with the IMFs from traditional VMD method. As we expected, traditional VMD is calculated from the current trace, which provides high resolution to the results but can't assure the lateral consistency. Even a small oscillation would totally change the decomposition results, which is always the drawback of high resolution decomposition methods---unstable. For seismic data, noise can't be fully suppressed and structural changes always happen. The IMF2 and IMF3 in Figure 6 are really hard to interpret. Figure 7 shows the IMFs from lateral consistency preserved VMD. The events in Figure 7c and 7d are more continuous and reasonable. Note, the events in Figure 7b-7d can be combined together to explain the reflector changes in Figure 7a, which can be helpful for seismic interpretation.

Discussions

Based on only the seismic data other than well logs, we adopt VMD to divide the sedimentary cycle and investigate its pattern. Sedimentary cycle is a good indicator of sequence stratigraphy, and will be really helpful for facies analysis (Li et al., 2016). Currently, machine learning facies analysis tools usually project multi-attributes to "potential spaces" without geology constraints. It doesn't mean researchers don't want to use seismic stratigraphic information, but because purchasing that kind of geology information is very time consuming. So if IMFs obtained from VMD can be used as a facies identification constraint, the classification results should be more reasonable. Another problem comes up: how to use the IMFs. Figure 5 shows the IMF1 is useful, but Li et al. (2016) decide IMF3 is the best in their application after cross-correlating the IMFs with well logs. To sum up, we want to just use seismic to perform some roles well logging is always acting, but well logs are still needed as the "answer".

Conclusions

Through synthetic comparison, we find VMD is better than EMD in current applications. Then, the modeling test and field application both show good results of sedimentary pattern identification. In order to better apply VMD on seismic applications, a lateral consistency preserved VMD method has been developed to respond to the challenges. It provides an improved lateral consistency, which enhances the quality and reliability of further analyses, such as seismic facies classification.

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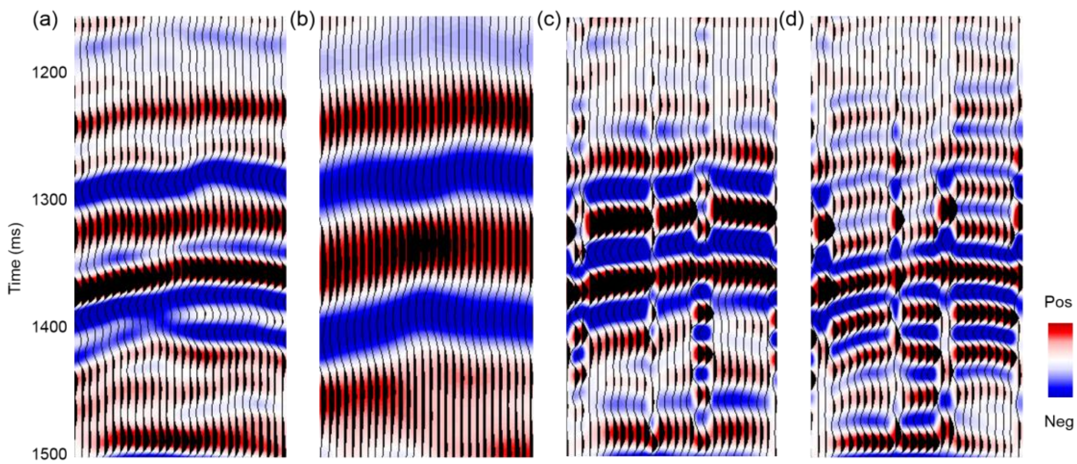

Figure 6: Example of traditional VMD. (a) Seismic and (b-d) different IMFs .

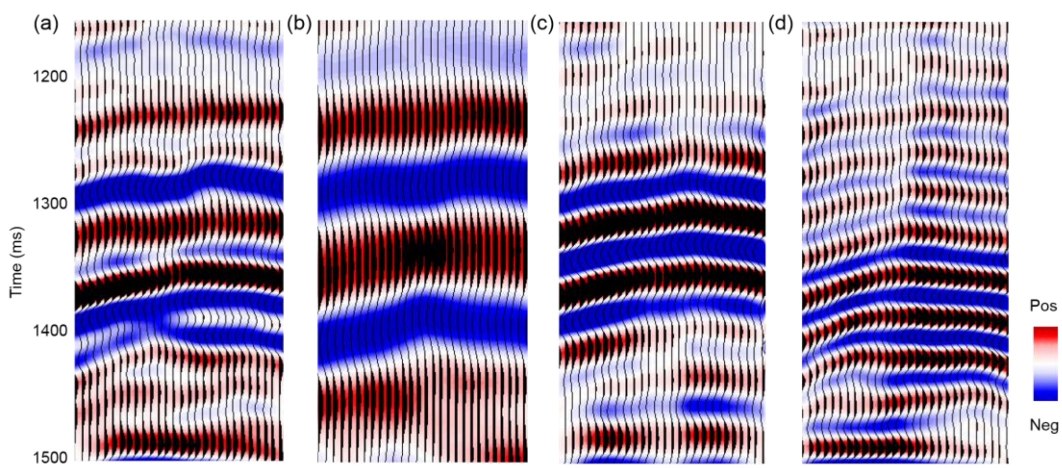

Figure 7: Example of lateral consistency preverved VMD. (a) Seismic and (b-d) different IMFs corresponded with thos in Figure 6.

EDITED REFERENCES

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