Under this regular column titled 'Expert Answers', we pose questions of both general and technical interest to well-known geophysicists who are considered authorities in a certain area within the geophysical domain and get their 'expert' answers. As these answers could have an individualistic tone, we request the answers from more than one expert in any area. To begin with, we have selected the following general question and include the answers given by Hongliu Zeng (Bureau of Economic Geology, The University of Texas at Austin), and Rui Zhang (School of Geosciences, University of Louisiana at Lafayette, USA). We thank them for encouraging us with their responses. Readers are encouraged to send us their feedback and even the questions they would like to get answered by experts.

The order in which the answers appear below is the order in which we received them.

- *Satinder Chopra*

Q. How have we addressed the problem of improving resolution of the seismic data over the last three decades, since 3D seismic data started getting adopted as a routine by oil companies?

Expert answer 1 by Hongliu Zeng*

Introduction

Resolution is a wide topic. As Reilly et al. (2023) correctly pointed out, we have to address multiple aspects of resolution to understand what it is and how to improve it, including various aspects of 3D survey design and acquisition, processing, and interpretation. During the last three decades, academia and industry have achieved tremendously in the first two areas. Designed for hydrocarbon exploration and development purposes, the modern seismic data are typically characterized by fairly high frequency range (from 10 to 70-100 Hz), zero- or constant-phase wavelet, correct subsurface positioning, and adequate signal-to-noise ratio (S/N). Assuming good data quality, this answer aims to address the third area: interpretation. I do not expect this answer to be thorough but do hope to inspire more discussions among colleagues.

Definition

To begin with, how do we define seismic resolution? There are at least three definitions based on different criteria (Figure 1). Based on a zero-phase wavelet and a wedge incased in a host of dissimilar impedance (e.g., a sand bed in shale), Widess (1973) claims the constant "peak-to-trough" traveltime at λ/8 (λ = dominant wavelength) is the limit of resolvability. Using a zero-phase wavelet and a stepwise, wedged impedance model (Figure 1b), Ricker (1953) argues the "flat spot" of composite waveform at < λ/4 should be defined as resolvable limit. Kallweit and Wood (1982) persuade most interpreters that the "peak-to-trough" separation of composite waveform at λ/4 is the most practical definition of resolvable limit. For a wedge with box

*Senior Research Scientist, Bureau of Economic Geology, The University of Texas at Austin.
Email: Hongliu.zeng@beg.utexas.edu

impedance profile (Figure 1a), this is also the "tuning point" where the maximum composite amplitude is observed. Clearly, the concept of resolution is related to human cognition to the geologic target. New concepts are possible in the future to fit new applications. We just have to keep an open mind. Also, the above-mentioned definitions are from idealized earth models, representing best possible, theoretical resolution. Practical (geological) resolution is not always as good as the theoretical one, owing, in part, to imperfect interpretation. Our task is to identify and solve problems for better practical resolution.

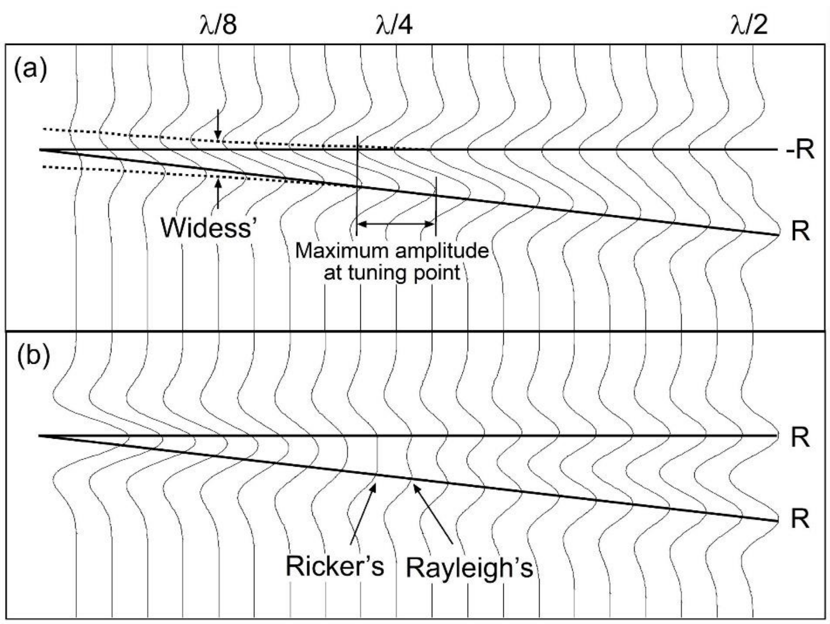

Figure 1. Three definitions of seismic resolution seen on wedge models. (a) Ricker wavelet model of a low-impedance wedge encased in high-impedance rock. (b) Ricker wavelet model of a wedge with stepwise-impedance profile.

Progress

For a given seismic data set (implying the data delivered to interpreters after processing), the main factors that control resolution include selection of attributes, the way to use frequency (bandwidth), and the wavelet shape in a certain geologic and geophysical formation (stratigraphy, structure, rock physics, and fluid content). People have done a lot in the last three decades to address those issues.

Choice of attributes: While seismic waveform (trace) is still the main platform for interpretation, we have been constantly searching for new seismic attributes for better resolution. (1) Many efforts have been made to identify distinguishing features for thin beds at or below seismic resolution. In addition to instantaneous attributes (Taner et al., 1979), frequency spikes (Zeng, 2010) and phase residues (Matos et al., 2011), as well as singularity (Liner et al., 2004; Li and Liner, 2005, 2008), Chopra and Marfurt's (2007) book summarized many useful attributes. (2) Another field is the generation of new attributes by extrapolating or reshaping bandwidth with poststack data, such as spectral inversion (e.g., Portniaguine and Castagna, 2004), spectral balancing (e.g., Fehmers and Höcker, 2003), pseudo deconvolution (Matos and Marfurt, 2011), and bandwidth extension (Smith et al., 2008).

Strategies to use frequency information: During the last three decades, analysis and application of seismic frequency information have had great advances. (1) Partyka et al. (1999) pioneered the spectral decomposition method by applying the short window discrete Fourier transform (SWDFT) to compute the spectral energy for time-frequency data volumes. (2) On another hand, the continuous wavelet transform (CWT) (Grossmann and Morlet, 1984) crosscorrelates a library of wavelets against a time series to construct localized frequency representations of a seismic trace in time, which is further improved by matching pursuit decomposition (MPD) for better vertical resolution (Mallat and Zhong 1992; Mallat and Zhang, 1993; Castagna and Sun, 2006). Removing interference of low-frequency components, the high-frequency subvolumes from these analyses can effectively increase seismic resolution for thin channels, etc. on stratal slices (examples in Chopra and Marfurt, 2006). (3) A more effective way is RGB colour blending of high-, moderate-, and low-frequency spectral components (Wessels et al., 1996) or seismic traces (frequency fusion or combination, Zeng, 2015). Especially, frequency fusion is more desired for stratigraphic and sedimentological reconstruction of a formation in vertical view by creating a geologically realistic display (mimic outcrop photos) that integrate thick and thin beds without significant interferences (Figure 2).

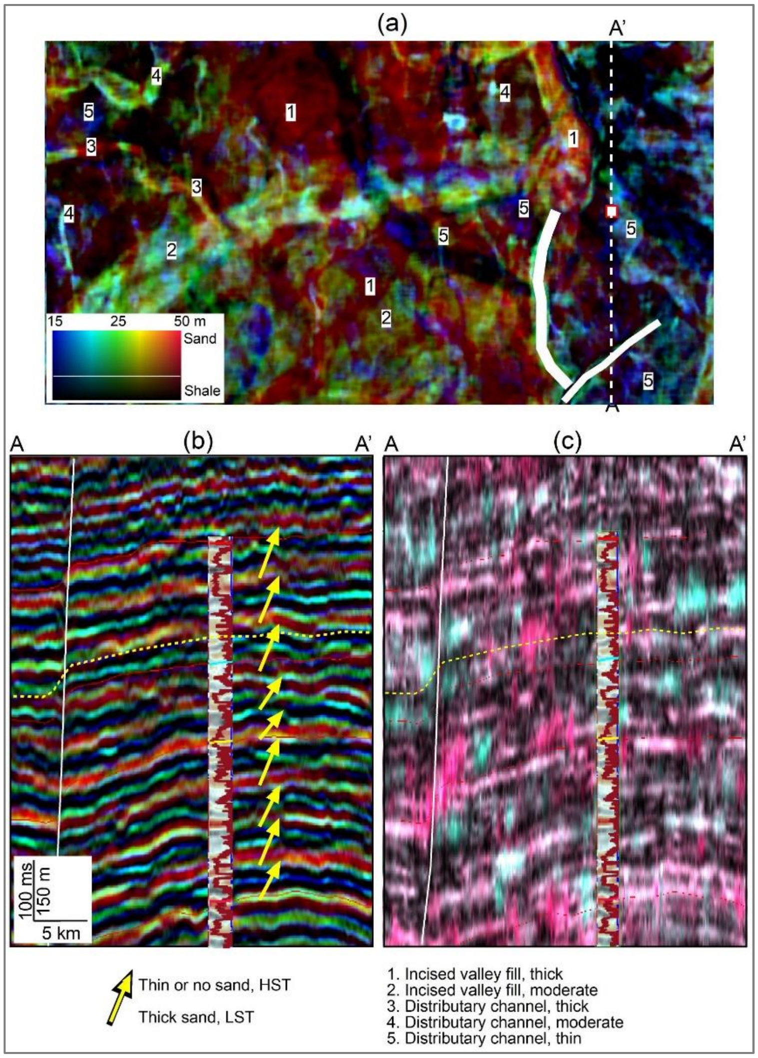

Figure 2. High-resolution stratigraphic and sedimentologic analysis achieved by RGB blending of three frequencies from a 90° seismic volume. A stratal slice (a) is made by blending 14-, 30-, and 50-Hz frequency panels with a wavelet transform algorithm. (b) Depositional facies, sand thickness (varying from 15 to 50 m in gamma ray log at well), and depositional cycles were controlled by systems tracts and sequence stratigraphy. (c) A blending of 14-, 30-, and 50-Hz iso-frequencies created with MPD is less ideal for stratigraphic imaging.

Wavelet shape and compactness: It is a "rule" for seismic interpreters that they should always use zero-phase wavelet because the symmetric waveform is the most compact and of the highest temporal resolution (Brown, 1991). However, this is true only if a single reflection surface is involved. In the case of a thin bed (typically with opposite but equal impedance contrasts at the top and base, Figure 1a), the composite waveform becomes antisymmetric, and the advantage of the symmetric wavelet no longer exists. Instead, a 90° wavelet can restore the symmetric waveform for a similar compactness and the best resolution. On comparing a stratal slice series made from 90° data to the slices from zero-phase volume in the same 3D survey, an interpreter will see fewer channel images on the 90° slice series because there is less vertical mixing of the stacked events. This technique is especially useful in an interfingered thin-bed formation.

From vertical to horizontal and spatial resolution: When processed (migrated) properly, a 3D seismic volume should have the horizontal resolution approximately equal to the vertical resolution (Lindsey, 1989). The value of both types of resolution in interpretation, however, depends on geology. The ratio of the horizontal versus the vertical dimension of a bed determines its spatial resolution status (Zeng, 2015). Most of the thin hydrocarbon reservoirs (especially sandstones) are characterized by a large horizontal dimension (tens to thousands of meters) and a small vertical dimension (meters to tens of meters), which are one-way resolved in the horizontal dimension, but are only detected in the vertical dimension. Such thin beds are volumetrically significant in both marine and lacustrine basins. Fortunately, such beds can be effectively imaged and evaluated by the use of seismic horizontal or stratal slices. These observations suggest that seismic interpretation of thin beds is restricted only to the detectable limit. Sheriff (2002) sets the detectable limit at $\lambda/25$. With recent improvements in data processing and interpretation, this number is outdated. Zeng (2011) observed in a case study that, with wire-line log verification, distributary channel sands as thin as one meter ($\lambda/80$) can be spatially resolved on the stratal slice (Figure 3).

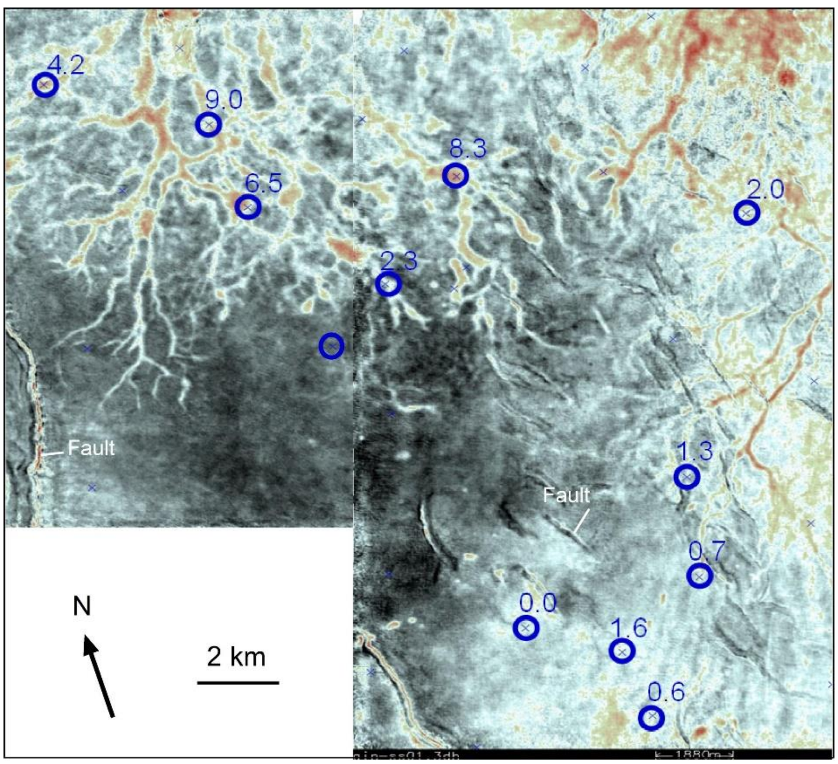

Figure 3. Optimal spatial resolution as revealed by a stratal slice made in a 50-Hz dominated frequency 3D volume in a lacustrine deltaic system. The thickness (m) of sandstone measured in gamma ray logs in wells shows a linear relationship with amplitude.

Future

Finally, a few points on the future direction of seismic resolution research: (1) We need to publish more model and case studies to validate useful thin-bed indicative attributes. (2) We should realize that pursuing high resolution is not a pure geophysical process; it needs more geologic support and integration. (3) Machine learning (ML) is a big thing these days. With a good-quality training data set, ML can "transfer" or "learn" high-resolution well information to between-well area by complex nonlinear combination of seismic attributes. This observation has been easily made with model testing (Figure 4). More studies are mandated to reveal detailed mechanisms.

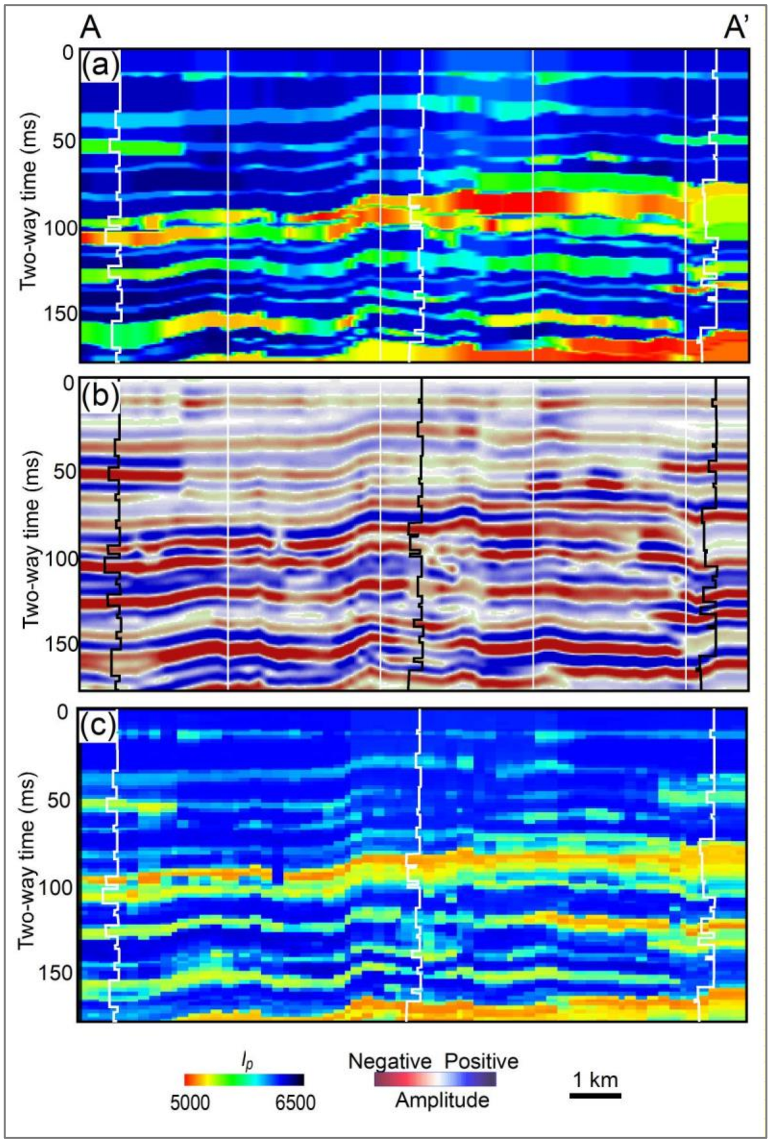

Figure 4. A test of ML-based inversion workflow (modified from Zeng et al., 2021). (a) A realistic acoustic impedance (I_p) model of an interfingered sandstone and shale formation. (b) 60-Hz, 90° Ricker synthetic model. (c) Testing results using a five-well-based large synthetic training data set. The logs in the three wells are for blind-testing purpose only.

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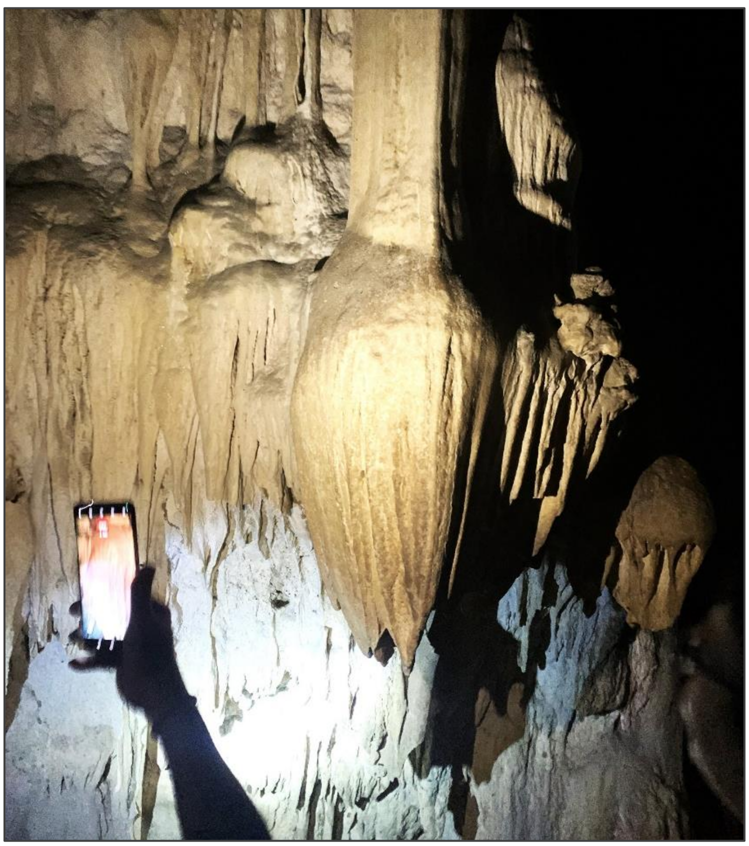
Hongliu Zeng is a senior research scientist in Bureau of Economic Geology (BEG), Jackson School of Geosciences, The University of Texas at Austin. His research interests include seismic sedimentology, seismic interpretation, and attribute analysis, with a focus on seismic resolution and thin-bed issues. He received a B.S. (1982), an M.S. (1985) in geology from the Petroleum University of China, and a Ph.D. (1994) in geophysics from the University of Texas at Austin. He is the primary author to win the Pratt Memorial Award from the American Association of Petroleum Geologists (AAPG) in 2005 for the work on frequency-dependency of seismic reflections as an indicator of geologic-time surfaces.



Stalactite in a limestone cave in Baratang Island (Andaman), India. A stalactite is an icicle-shaped formation with a pointed tip, that hangs from the ceiling of a cave and is produced by precipitation of minerals from water dripping through the cave ceiling. (Photo courtesy: Ritesh M. Joshi)

Expert answer 2 by Rui Zhang*

Seismic resolution remains an enduring subject that has continually embraced innovative insights over the decades, as it wields a direct influence on subsurface interpretation, particularly in the context of thin reservoir beds. In this article, we will discuss the techniques that can improve the resolution of the poststack seismic data. The discourse on seismic resolution traditionally commences with the seminal work of Widess (1973) In this pivotal article, the delineation of seismic resolution confines itself to a quarter wavelength (λ/4) in terms of two-way travel time, where a stratum measuring less than a threshold of λ/8 assumes the classification of a thin-bed, colloquially referred to as a "tuning thickness." This implies that layers falling beneath this threshold emerge as challenging to distinguish. The paper further underscores the feasibility of detecting or characterizing these thin-beds through various techniques. One illustrative method involves employing the tuning curve, which allows for the determination of thin-bed thickness by virtue of its integrated amplitude response. Presented in Figure 1 are two instances spotlighting predominantly even and odd wedge models, each accompanied by their respective tuning curves. In scenarios where the top and base reflection coefficients bear identical polarity, a constructive composite amplitude surfaces when thickness is less than the turning point, exemplified in Figure 1a; conversely, Figure 1b reflects the converse situation. It is important to note, however, that this technique can be influenced by the sidelobe of the estimated wavelet, potentially giving rise to inaccuracies in thickness estimation.

Deconvolution was one of the first developed seismic data processing techniques based on the convolution model. The convolution model assumes that seismic trace (s) is the convolution result of reflectivity (r) and wavelet (w) with addition of noise (n), as shown in Equation (1). "∗" represents the convolution operation.

$$s(t) = r(t) * w(t) + n(t) \quad (1)$$

The corresponding frequency domain expression is shown below.

$$S(\omega) = r(\omega) \times w(\omega) + n(\omega) \quad (2)$$

The convolution model is based on seven assumptions (Yilmaz, 2001), namely, (1) The earth is made up of horizontal layers of constant velocity, (2) the source generates a compressional plane wave that impinges on layer boundaries at normal incidence. Under such circumstances, no shear waves are generated, (3) the source waveform is known, (4) the source waveform does not change as it travels in the subsurface - it is stationary, (5) the noise component n(t) is zero, (6) reflectivity is a random process. This implies that the seismogram has the characteristics of the seismic wavelet in that their autocorrelations and amplitude spectra are similar, and (7) the seismic wavelet is minimum phase. Therefore, it has a minimum-phase inverse.

Deconvolution aims to recover the reflectivity (r) with improved resolution by convolving an operator (f), also called an inverse filter or inverse wavelet, with seismic trace (s). Theoretically, the convolution result of the operator (f) and wavelet (w) would be a delta (δ) function.

*Associate Professor in geophysics, University of Louisiana at Lafayette. Email: rui.zhang@louisiana.edu

$$f(t) * w(t) = \delta(t); \; f(t) = w^{-1}(t) \qquad (3)$$

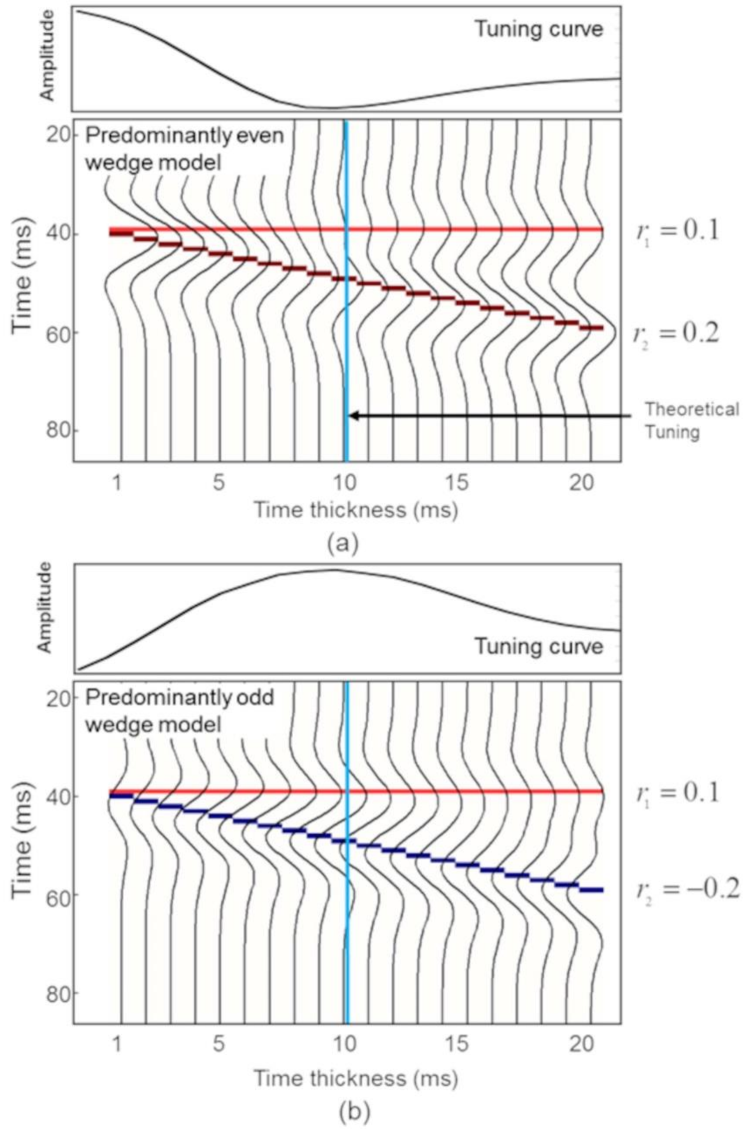


Figure 1: Predominantly even and odd wedge models. (a) Predominantly even wedge model and its tuning curve with seismic responses overlaid. (b) Predominantly odd wedge model and its tuning curve with seismic responses overlaid. Seismic responses are generated with a 40-Hz Ricker wavelet convolved with the wedge reflectivity. The tuning thickness is 10ms. (Zhang and Castagna, 2011)

If all seven assumptions hold true, the process of deconvolution becomes a straightforward endeavor, resulting in the recovery of accurate reflectivity through the utilization of the estimated wavelet obtained from seismic data and its subsequent inversion. However, the practical reality is that these seven assumptions often fall short of being completely valid. Consequently, the effectiveness of deconvolution hinges on the strategies employed to address these discrepancies and arrive at a precise estimation of the wavelet, as well as a stable inverse filter.

The construction of the inverse filter typically involves minimizing the Lp norm of the discrepancy between forward modeling and the actual data with constraint. In instances where p equals 2, the derivation of the inverse filter adheres to the principles of the classic least-squares approach, as elucidated by (Berkhout, 1877). However, when p assumes a value below 2, the inverse filter yields a reflectivity characterized by sparse-spike patterns, as demonstrated by the works of Taylor et al. (1979), and Levy and Fullagar (1981).

Assumptions 1 and 2 primarily pertain to acquisition and migration techniques, aspects which are not delved into within this discussion. Assumption 3, recognized as the stationarity assumption, has been a focal point of study due to seismic waveforms undergoing shifts in amplitude, frequency, and phase as they traverse the subsurface. A pertinent example is the incorporation of the attenuation factor Q, which characterizes energy decay during seismic wave propagation, into the formulation of the time-varying deconvolution operator (f). This integration serves to counteract energy loss, enhancing reflectivity accuracy, as demonstrated by (Margrave, 1998). This contribution prompted the consideration of spectrum variations in seismic data arising from dispersion effects.

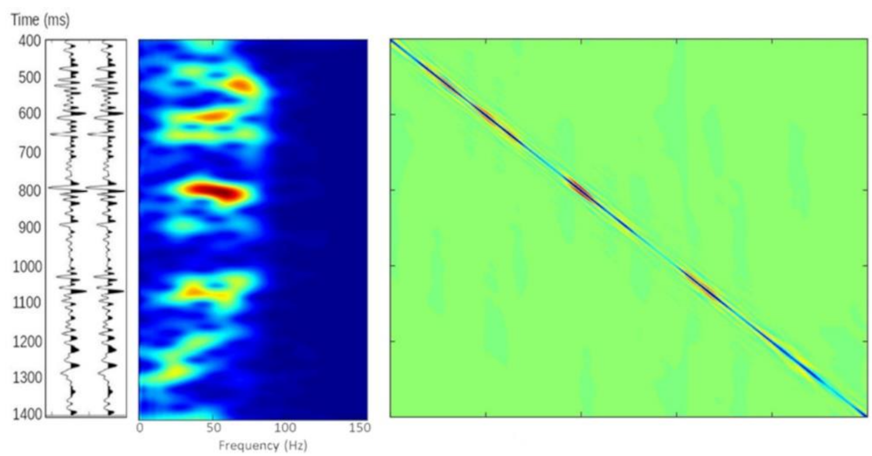


Figure 2: A example seismic trace in the left panel; its spectral decomposition result in the middle panel; wavelets kernel matrix in the right panel (Zhang and Fomel, 2017).

Zhang and Fomel (2017) introduced a systematic approach to extract time-varying wavelets, harnessing the outcomes of S-transform-generated time-frequency decomposition, illustrated in Figure 2. The left panel replicates a seismic trace, while the middle panel showcases the corresponding time-frequency decomposition outcomes achieved through the S-transform technique. Notably, the right panel depicts the extraction of time-varying wavelets from these decomposition results, arranged along the diagonal of a square matrix. This innovation showcases a refined perspective on addressing the non-stationarity inherent in seismic data.

Seismic data inherently incorporates noise, rendering assumption 4 less tenable. In practice, this noise is typically treated as stochastic with a white spectrum, consequently aligning with the least-squares approach. An essential factor in achieving optimal deconvolution outcomes involves possessing *a priori* understanding of the noise level. The accurate calibration of this noise level proves critical, as misjudgment can introduce bias into the estimated wavelet, thereby amplifying noise within the deconvolution result. Coherent noise compounds this challenge, particularly in situations where the estimation of the wavelet encompasses spectral elements of such noise. In these scenarios, a judicious approach involves excluding specific noises, such as multiple reflections, which could be suppressed via deconvolution when the operator is thoughtfully defined utilizing primary reflection data.

Assumptions 5 and 6 share a close relationship when it comes to wavelet estimation. The stochastic presumption regarding reflectivity engenders parallelism between the autocorrelation spectra of the wavelet and seismic data, constituting a classic method for wavelet estimation. The reflectivity's broader spectrum compared to seismic data permits its consideration as stochastic within the seismic spectral range. Nonetheless, instances where the reflectivity defies stochasticity necessitate its integration into wavelet estimation. For instance, well-log data can be coupled with seismic data to derive a calibrated wavelet conducive to deconvolution or inversion procedures. This approach is particularly advantageous in situations where the stochasticity assumption does not align with the characteristics of the subsurface.
Assumption 7 of minimum phase is important for obtaining stable deconvolution result, because a maximum phase wavelet could result in unstable result. This assumption can be accomplished during the wavelet estimation with phase rotation.

In addition to deconvolution methods, another pivotal approach for improving resolution in seismic imaging is inversion techniques. These techniques are often formulated as iterative solutions of linear equations. While iterative inversion procedures tend to exhibit greater stability compared to operator-based deconvolution, they do demand more computational time.

The equation describing the relationship between the seismic trace (denoted as 'y'), the kernel matrix ('A'), and the solution ('x') is given by:

$$\mathrm{y} = \mathrm{Ax} \tag{4}$$

In instances where the matrix 'A' is constructed as a diagonal wavelet matrix, like the depiction in the right panel of Figure 2, the solution corresponds to reflectivity. The least-squares solution is attained by minimizing the L2-norm or root-mean-square error between the forward-modeled data and the actual data, as depicted in the equation below:

$$\min \|\mathrm{y} - \mathrm{Ax}\|_2 \tag{5}$$

Another advantage of the least-squares solution is its adaptability in incorporating various forms of pre-existing information, enabling the derivation of distinct subsurface properties with enhanced resolution. For instance, an acoustic impedance model at low frequencies can be integrated into the 'A' matrix, yielding a subsurface acoustic impedance solution (Oldenburg et al., 1983). Puryear and Castagna (2008) introduced a spectral inversion method that employs frequency-domain responses of dipole reflections as basis functions, facilitating the resolution of thin-bed layers. Zhang and Castagna (2011) developed a sparse layer inversion technique, which integrates dipole decomposition using a basis pursuit inversion scheme to achieve inverted reflectivity with improved resolution. The basis pursuit algorithm, a method that minimizes the L1 norm, demonstrates exceptional performance and stability in this context.

$$\min [\|y - Ax\|_2 + \lambda \|x\|_1] \quad (6)$$

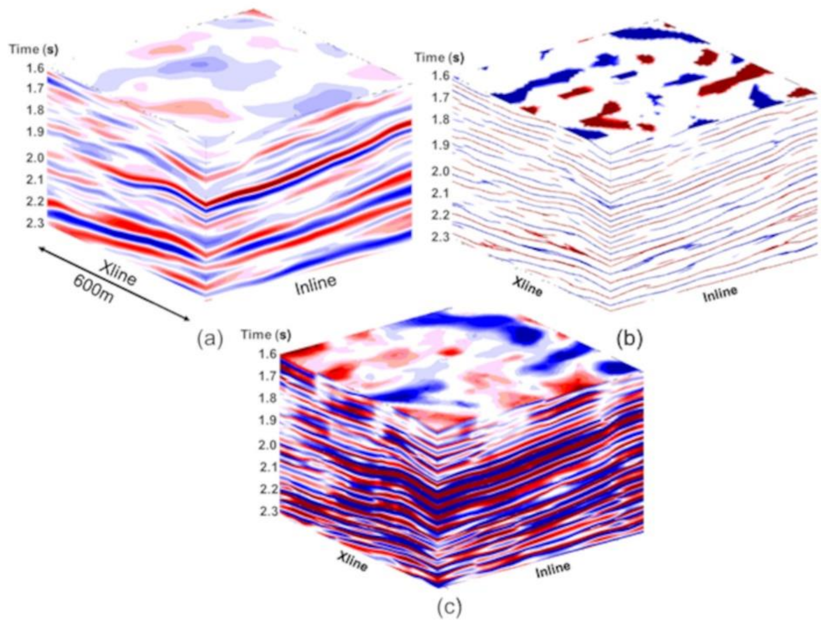


Figure 3: (a) shows a 3D seismic volume. (b) shows inverted reflectivity by using the basis pursuit method with incorporation of the dipole decomposition. (c) shows the relative impedance derived from the inverted reflectivity Zhang and Castagna (2011).

The inverted reflectivity consistently exhibits superior high resolution, as depicted in Figure 3b. Additionally, Figure 3c illustrates a relative impedance volume derived from the reflectivity, often referred to as band-limited impedance in existing literature. Notably, the relative impedance volume also demonstrates higher resolution than the seismic data itself, revealing a layered structure that greatly appeals to geologists, in contrast to the reflectivity which primarily represents the layer boundaries.

Both deconvolution and inversion methods have traditionally been applied to time domain seismic data. However, in contemporary seismic imaging, there is a growing adoption of depth domain migration techniques to acquire seismic data in depth coordinates. This shift raises the question of whether the techniques can be directly applied to depth domain data. In response, the answer is a definitive "Yes," albeit with some necessary modifications.

One pivotal aspect involves transitioning from time-frequency domains to depth-wavenumber domains. This alteration is crucial, as it facilitates the direct implementation of many spectral expansion techniques on depth domain seismic data Zhang and Deng (2018). By embracing this paradigm shift, seismic imaging techniques can be refined to better capture subsurface structures and properties in the depth dimension.

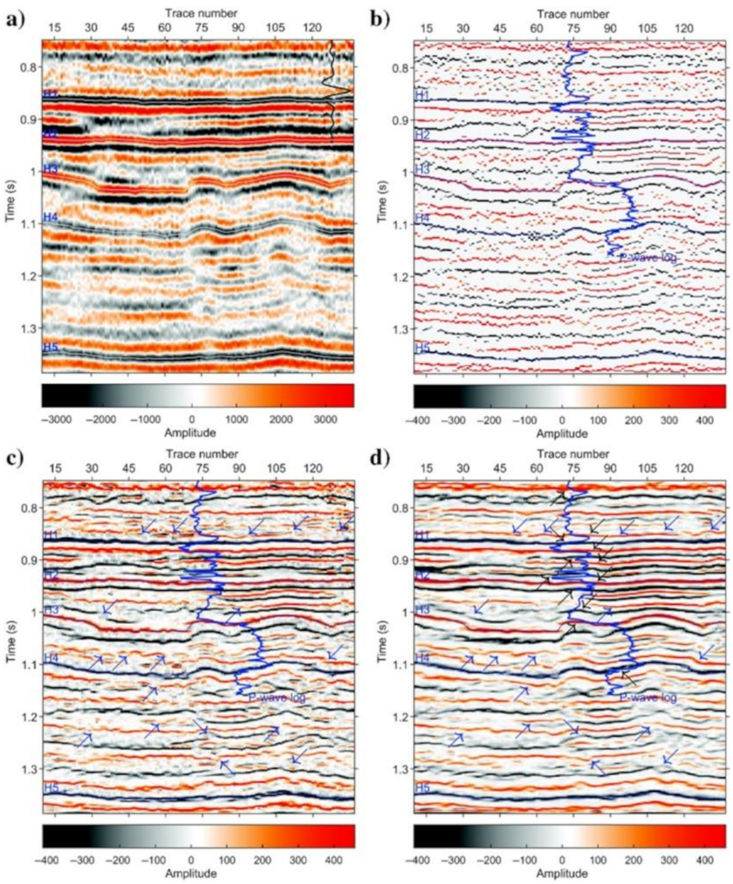


Figure 4 (a) shows a cross-section of 3D Erskine data. (b) shows inversion result by conventional trace-by-trace sparse-spike inversion method. (c) shows results of the 2D CNN prediction. (d) shows results of the 3D CNN prediction. (Chai et al., 2021)

In recent years, the integration of machine learning techniques has emerged as a transformative approach to significantly enhance seismic resolution. Leveraging the computational prowess of machine learning algorithms, seismic data can be processed and interpreted with unprecedented precision. These techniques enable the extraction of subtle subsurface features that might be challenging to discern using traditional methods alone. Machine learning models, such as deep neural networks and convolutional neural networks, excel at learning intricate patterns within seismic data and effectively denoising or deblurring images. Moreover, they can aid in overcoming limitations associated with acquisition noise, incomplete data, and complex subsurface structures. By training on extensive datasets, machine learning algorithms can infer complex relationships between seismic attributes and subsurface characteristics, leading to high-resolution reconstructions that provide geoscientists and engineers with a more detailed understanding of the Earth's subsurface. Chai, et al., (2021) introduced a workflow to derive reflectivity from data by training end-to-end encoder-decoder-style 2D/3D convolutional neural networks (CNN). Figure 4 shows comparison between Sparse-spike inversion results (Figure 4b) and CNN results (Figures 4c and d).

As the field of machine learning continues to advance, its potential to revolutionize seismic imaging and interpretation remains a promising frontier in the pursuit of enhanced resolution and accuracy.

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Rui Zhang is Associate Professor in geophysics, holding John E. and Joretta A. Chance Endowed Professorship, at the School of Geosciences, University of Louisiana at Lafayette. He received his Ph.D. in Geophysics in 2010 at University of Houston followed by two postdoc fellow experiences at the University of Texas at Austin and Lawrence Berkeley National Laboratory. Rui's Ph.D. dissertation was working a basis pursuit inversion technique to obtain high resolution seismic reflectivity with incorporation of sparse layer dictionary. The method was later extended to pre-stack and depth domain seismic data successfully. Rui's research interest also covers geophysical application on energy transition, including carbon capture and storage (CCS), enhanced geothermal system (EGS), hydrogen geological storage, and wind farm site characterization. Rui is the winner of the Best Paper Award of Interpretation in 2018 and Best Poster Paper presented at the Annual SEG Meeting in 2020.