UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

SEISMIC ATTRIBUTES: TAXONOMIC CLASSIFICATION FOR PRAGMATIC MACHINE LEARNING APPLICATION

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

DUSTIN THOMAS DEWETT
Norman, Oklahoma
2021

SEISMIC ATTRIBUTES: TAXONOMIC CLASSIFICATION FOR PRAGMATIC MACHINE LEARNING APPLICATION

A DISSERTATION APPROVED FOR THE SCHOOL OF GEOSCIENCES

BY THE COMMITTEE CONSISTING OF

Dr. John Pigott, Chair

Dr. Kurt Marfurt, Co-Chair

Dr. Zulfiquar Reza

Dr. Younane Abousleiman

Liz, thank you for putting up with me, the children have no choice, but it means a lot that you stuck with me all of these years. Also, the kids are pretty great.

Acknowledgements

I would like to acknowledge, first and foremost, the group of people in my life who I cannot live without, my wife and children, Elizabeth, Glorianna, Lailani, Thomas, Catherine, and Tyrion; while it is true that without these people, this work would never have been completed, it also would have been faster if I didn't play so many video games with them; I would be remiss if I failed to mention my advisors, John Pigott and Kurt Marfurt; I also benefited, in no small part, from the sometimes enlightening, and always entertaining, John Castagna, one of the single greatest scientists that I have ever known, Fred Hilterman, and, perhaps, the greatest group of people ever assembled in a single room, the Quantitative Interpretation Group, which no longer exists, at BHP, which is no longer, Billiton; I was unable to have Fred Hilterman on my committee, because of bureaucratic nonsense, I dropped John Castagna following the merger of both a rule change at The University of Oklahoma and the realization that he is, probably, one of the most difficult to schedule people that I know; I hope that he never took offense to that.

I received support from BHP Billiton, which was, in reality, only Dr. Andy Pepper, Richard Keen, and Dr. Mauricio Flores, who are all great people. I am sorry that only one of you still work there; you all got a raw deal. Niall is an idiot, and Mike is a liar.

Table of Contents

List of Tables

List of Figures

Abstract

Seismic interpretation involves more than simply picking faults and horizons. It involves the interpretation of geologic features — their geometry, morphology, and the context of one group of rocks to another. It involves using well log information, memories from fieldwork, and photos from outcrops. It involves the understanding of salt mechanics, wave propagation, and signal analysis. It requires context and agile minds that can readily distinguish mud volcanoes from salt diapirs or multiples from reflectors. It is a difficult practice, and individuals spend their entire careers devoted to it.

Seismic attributes have always been considered by many to be an art form — a "dark art" — practiced by a chosen few. The proliferation of attributes to the workstation has not, unfortunately, proliferated the understanding of what the attributes mean or of what they are capable. Today, you will often find the seismic attribute specialists in quantitative interpretation or computational geophysics groups. The perspective of these specialists and of general interpreters can be quite different. They understand both physics and geology in different ways and at different levels.

As the discipline moves toward new technologies and the promises of new algorithms like convolutional neural networks and other forms of machine learning, we must remind ourselves that the technical understanding required of scientists and professionals grows accordingly. However, like the proliferation of seismic attributes (e.g., geometric and single-trace), machine learning approaches will feel underwhelming by those who fail to understand both the algorithms and what can reasonably be achieved.

This dissertation provides the reader with the foundational knowledge one requires to begin to understand seismic attributes and how they can be used with machine learning algorithms. I begin by establishing a common framework on which to communicate. I build upon that through the development of a procedure to enhance faults in seismic data using commercially available tools, and I end with the introduction of a simple, but effective, use of self-organizing maps, a simple machine learning algorithm.

Chapter 1: Introduction

Seismic attributes are used by the majority of seismic interpreters, whether they are academics or professionals. Many present-day seismic interpreters begin their career during the initial a period that Chopra and Marfurt call the "Proliferation of Attributes" in the 1980s to the 1990s (2007). As time progresses, the percent of seismic interpreters that this group represents shrinks, and they are replaced by a group of interpreters who have little knowledge of seismic attributes beyond what is available in the particular commercial software that they use. This younger group is the largest adopter of new techniques using machine learning (e.g., convolutional neural networks, support vector machines, etc.). However, without a firm understanding of basic seismic attributes (theory, best practices, etc.), often these younger scientists and professionals understand these results as a type of deterministic answer. Even seasoned scientists and professionals can fall into this trap, as evidenced by recent claims in the literature (Leal et al., 2019; Roden and Chen 2017; Roden et al., 2015; Roden et al., 2017; Sacrey and Roden, 2016; Sacrey and Roden, 2018; Santogrossi, 2016). Work by Barnes (2017), designed to counter the claims of extraordinary claims of increased seismic resolution when using self-organizing maps (SOMs) has been unanswered by the original proponents. As we move into this new era of seismic interpretation, we must remember that a firm understanding of the base principles in geophysics, algorithms, and historical useage patterns remain not only important but critical.

In Chapter 2, I investigate began by asking how and why we group attributes together. I was concerned with how geoscientists are educated on the usage of seismic attributes, and, after attending every significant course available, I realized that we use different terminology to discuss groups of seismic attributes based on our background. When I investigated the literature, I found that my preferred attribute groupings were not preferred by my peers. In developing this chapter, I still have lingering questions that are both simple and unanswered.

- How many of the claims of a given attribute aiding various interpretation goals are verifiable?
- Of these verifiable claims, are some attributes objectively superior?
- How have the use of given seismic attributes changed over time, and what has caused those changes?
- What can these unverifiable claims and "over interpretations" teach us about the use of machine learning algorithms going forward?

While this dissertation does not directly answer these questions, it does provide a step toward understanding the limits of emerging machine learning technologies, potential pitfalls, and underscores the need to comprehend both what the machine is doing on our behalf and if this is an intelligent application of this technology.

In Chapter 3, I develop a method of incorporating spectral decomposition and any given seismic attribute into a fault enhancement technique. This method is novel in two ways. First, it is the first known use of spectral decomposition phase, magnitude, and any arbitrary seismic attribute (computed on the band-limited seismic) to improve fault definition and reduce noise in a single seismic volume. This method was performed through a creative use of existing algorithms. Since its original publication, it has been cited by researchers 23 times. It has prompted entire lines of research at both the University of Oklahoma and the University of Houston, and a similar algorithm (i.e., an attempt to duplicate these results) now exists in two different software packages.

In Chapter 4, I ask, “What value can a SOM used as a classification method give to a seismic interpreter?” The answer was an interesting use of a SOM using only two seismic attributes derived from band-limited seismic inversion. To date, this is the only paper discussing the practical use of SOMs using only two attributes. What this shows is that given a minimal amount of understanding, a seismic interpreter who is untrained in quantitative seismic interpretation (QI) can use the outputs from a seismic inversion to perform rapid reconnaissance on a volume, which will reduce the time required for a QI specialist to verify. This technique effectively empowers a general seismic interpreter to see their data how specialists do. Additionally, it also shows that there is potential value in reducing the number of attribute used in unsupervised classification techniques. An area where it is common for interpreters and researchers to use half a dozen to a dozen attributes.

References

Barnes, A. 2017. "Instantaneous Attributes and Subseismic Resolution." In *SEG Technical Program Expanded Abstracts*, 2018–22. SEG Technical Program Expanded Abstracts. Society of Exploration Geophysicists. https://doi.org/10.1190/segam2017-17583126.1.

Chopra, S., and K. J. Marfurt, 2007, Seismic Attributes for Prospect Identification and Reservoir Characterization: Society of Exploration Geophysicists.

Leal, Jonathan, Rafael Jerónimo, Fabian Rada, Reinaldo Viloria, and Rocky Roden. 2019. "Net Reservoir Discrimination through Multi-Attribute Analysis at Single Sample Scale." *First Break* 37 (9): 77–86. https://doi.org/10.3997/1365-2397.n0058.

Roden, R., and C. W. Chen. 2017. "Interpretation of DHI Characteristics with Machine Learning." *First Break*, 2017. http://www.earthdoc.org/publication/publicationdetails/?publication=88069.

Roden, R., T. Smith, and D. Sacrey. 2015. "Geologic Pattern Recognition from Seismic Attributes: Principal Component Analysis and Self-Organizing Maps." *Interpretation* 3 (4): SAE59–83. https://doi.org/10.1190/INT-2015-0037.1.

Roden, Rocky, Thomas A. Smith, Patricia Santogrossi, Deborah Sacrey, and Gary Jones. 2017. "Seismic Interpretation below Tuning with Multiattribute Analysis." *The Leading Edge*, April 1, 2017. https://doi.org/10.1190/tle36040330.1.

Sacrey, D., and R. Roden, 2016, Multi-attribute seismic analysis in Paradise: Application of unsupervised neural networks and principal component analysis in conventional and unconventional geologic settings: Geophysical Insights white paper.

Sacrey, Deborah, and Rockey Roden. 2018. “Solving Exploration Problems with Machine Learning.” *First Break* 36 (6): 67–72. https://doi.org/10.3997/1365-2397.n0100.

Santogrossi, P., 2016, Case studies in sub-seismic resolution: Geophysical Insights white paper.

Chapter 2: A Review of Seismic Attribute Taxonomies

Beginning in the 1970s, seismic attributes have grown from a few simple measurements of wavelet amplitude, frequency, and phase to an expanded attribute toolbox that measures not only wavelet properties but also their context within the 3D seismic volume. When using multiple seismic attributes, the interpreter must understand not only each individual attribute but also the relationships between them. Researchers communicate these relationships via seismic attribute taxonomies, which group attributes by their signal property, mathematical formulation, or their interpretive value. The first attempts to organize seismic attributes began in the 1990s, and with new attributes and their increasing breadth of applications, continues to this day. Most scientific papers that use seismic attributes focus on a specific application, new algorithms, or a novel interpretation workflow, rather than how a specific attribute fits within the greater whole, leading to confusion for the less experienced interpreter. We have analyzed more than 2100 citing works, identified the 231 papers that discuss the taxonomies specifically, and found out how the authors use those citations. The result is a list of more than a dozen seismic attribute classification systems, which we reduce to a smaller subset by including only those that apply to general use. An optimal seismic attribute taxonomy should not only be useful to the interpretation community today, but it should also adapt to the ever-changing needs of the profession, including changes appropriate for their use in modern machine-learning algorithms. The adaptability of prior work to modern workflows remains a shortcoming. However, as we develop our work in two parts — the first covering the evolution of seismic attribute taxonomies and their use through time and the second proposing a new seismic attribute communication framework for the larger community — we link attributes together via data analysis principles and provide an extensible model as the profession and research expand.

Introduction

The most familiar seismic attribute used by modern seismic interpreters is poststack seismic amplitude; however, most seismic interpreters omit seismic amplitude and consider seismic attributes to involve a nontrivial computation on these data. We define seismic attributes as the infinite number of mathematical permutations, algorithms, or observable features that can segment, filter, classify, or describe the seismic waveform, a subset thereof, by itself or in the context of neighboring, conterminous, or diachronic waveforms. We define a seismic attribute taxonomy as the system or framework used to group seismic attributes for the purpose of communicating ideas on their use. We use this term synonymously with scheme, schema, framework, grouping, and other similar terms.

Seismic attribute analysis is a specialty in exploration geophysics that appears crowded and complex owing to the proliferation of attributes in number, purpose, and algorithmic implementation. Seismic attributes are powerful interpretation tools that allow data segmentation and geologic pattern enhancement. Their utility is clear, given that seismic interpreters continue to use seismic attributes to interrogate their data at a rate that places attribute analysis as one of the most used techniques in contemporary interpretation workflows.

We find that general seismic interpreters often lack a background in physics, mathematics, or computer programming that would help them understand the many attribute algorithms that contain mathematics and algorithmic approaches that are nontrivial. With many algorithms approaching a staggering level of complexity, general seismic interpreters adopt their understanding of seismic attributes via observed usage and experience, whereas their research counterparts are often more comfortable using mathematics as their foundation. The result is a fractured, partially informed, and inefficient seismic interpretation community, which often results in the misuse of seismic attributes, their information, and, ultimately, an interpretation susceptible to confirmation bias.

The most productive seismic interpretation projects involve interdisciplinary teams of which seismic attribute experience and expertise play a significant, yet secondary or tertiary, role. One obvious benefit from such a team is the natural reduction of potential sources of bias. However, the modern seismic interpreter, academic and professional, faces a nearly incomprehensible level of information, some of it duplicate, in a form that few receive the training to digest properly. Moreover, because scientists use different software packages, possess a fractured understanding of geophysical theory, or use different interpretation practices, communication silos are the norm rather than the exception. Furthermore, communication difficulties between the research community and the day-to-day practitioner, as well as among practitioners from different companies, are all too common. Using more succinct phrasing, we claim that a philosophical and methodological understanding exists behind any attribute, with the philosophical being expressed in the designed function and actual use and the methodological being represented by the particularities of an algorithm, driven by mathematics. These different viewpoints account for many of the communication difficulties that we observe in our academic and professional roles. Therefore, there is an acute need for improved channels of communication. Through our combination of experience and historical analysis, we submit a seismic attribute communication framework to aid in the endeavor.

To this end, we have identified 10 notable seismic attribute classification schemes in the scientific record. Although we identified more that technically exist, their authors' purpose of those omitted was narrow in context and did not apply to a more general audience. These 10 classifications are those presented by Taner et al. (1994), Carter (1995), Brown (1996) with later edits (2011), Barnes (1997), Chen and Sidney (1997a, 1997b), Taner (2001), Randen and Sønneland (2005), Liner et al. (2004) republished in (2016), Barnes (2016), and Marfurt (2018).

The authors of each of these schemes built upon the techniques used by the seismic interpreters at the time of their publication and by the inherent bias present in how each author used seismic attributes in their interpretation work or research. As we investigated the historical (publication) record, we segmented the seismic interpretation timeline into three chronological periods: the instantaneous attribute period (c. 1977–1997), the quantitative attribute period (c. 1997–2020), and the artificial and expert systems period (c. 2020 onward). Such an organization reinforces important historical context that affected the original author's thought processes, and it is how we begin this study.

To understand patterns in the usage of each seismic attribute taxonomy, we borrowed concepts from the field of data analysis to describe the bias of seismic interpreters and researchers owing to their mental perspective of the topic. "Data analysis" is a term defined by Tukey (1962) as the "procedures for analyzing data, techniques for interpreting the results of such procedures, ways of planning the gathering of data to make its analysis easier, more precise or more accurate, and all the machinery and results of (mathematical) statistics which apply to analyzing data." The "Data analysis domains" section provides details on these concepts. We arrived at the following conclusions from our historical analysis:

1. An author's data analysis domain, presented implicitly through their taxonomy, provides value to researchers and professionals who have different communication styles and thought processes.
2. The historical taxonomies lack adaptability to modern workflows and newer algorithms.
3. Most of the attributes used in the historical taxonomies are out of date; however, these out-of-date taxonomies may not always be as significant of a problem as one would expect.
4. While perhaps always implicit, researchers have adopted the concept of useless seismic attributes as a motivating factor in the development of seismic attribute groupings, which presents a source of bias that affects the work by all authors since its formal introduction.

In the practical section of this paper, titled "Creating useful seismic attribute taxonomies," we will use our observations and conclusions from the historical section to develop and present a communication framework that comprises a seismic attribute taxonomy for each data analysis domain and associated cross-referenced charts. Our proposed communication framework has the following features:

1. a seismic attribute taxonomy for each data analysis domain with example attributes that facilitate communication and understanding regardless of one's data analysis perspective
2. a list of 35 example attributes in all taxonomies, a cross-referenced chart, and a table of basic definitions for each
3. visual cues, such as color or hierarchy, which reinforce the organization of each taxonomy
4. a curated list of examples, allowing readers to identify where missing attributes, historical and contemporary, easily fit into our communication framework.

Finally, we identify where this work is lacking and discuss methods to mitigate these problems with future work.

Historical Context

Chronological History of Attribute Taxonomies

The instantaneous attribute period (c. 1977–1997)

We define the instantaneous attribute period by the recognition that a suite of single-trace attributes based on the analytic (or complex) seismic trace could have value not only in seismic processing but also in interpretation. Such measures of reflection strength, frequency, and phase provided some additional interpretational value on vertical seismic sections. Their value was most significant when viewed on time and horizon slices through 3D data volumes and interpolated maps of 2D data grids, in which visualization of the seismic wavelet is not possible.

Seismic interpreters primarily used seismic data to map geologic structure. Rummerfield (1954) is perhaps the first to recognize that the information contained within the seismic waveform held information regarding the lithology, porosity, and fluids in the waveform's "quality." However, it was Taner and Sheriff (1977) and Taner et al. (1979) who first present a pragmatic application of attributes based upon insights from electrical engineering that drove the earliest and most significant rise in seismic attribute usage among professional interpreters.

Rijks and Jauffred (1991) introduce attributes computed from the horizon including reflector dip magnitude and azimuth, where others introduced formation-based attributes such as root-mean-square (rms) amplitude, maximum peak amplitude, maximum trough amplitude, average absolute amplitude, number of zero crossings, and other measures between two picked or implied horizons. Like instantaneous attributes, the formation-based attributes are measured on a single-trace, whereas the horizon-based attributes do not require seismic data following the generation of a surface.

Taner et al. (1994) propose the first significant attempt to organize seismic attributes (Figure 2.1). The work in seismic stratigraphy, dominated by the work of the 1970s, significantly influenced Taner et al. (1994), the development of seismic attributes, and the organization thereof. The authors also discuss prestack attributes; however, they mute the discussion, compared to that of seismic stratigraphy. This is an interesting historical point because modern geophysicists would place a significantly heavier weight on prestack attributes owing to the formalized theories of amplitude variation with offset (AVO) and seismic inversion (Castagna and Backus, 1993) and the now well-documented case studies that place prestack seismic analysis as the dominant technique in quantitative seismic interpretation (Hilterman, 2001; Chopra and Castagna, 2014; Thomsen, 2014). The authors provide two major divisions: geometric attributes and physical attributes. The geometric attributes, in this view, are used to understand the morphology between the seismic reflectors, whereas the physical attributes correlate to rock properties.

Carter (1995) emphasizes using seismic attributes to aid seismic facies mapping and presents a mental framework in which attributes are windowed or not (Figure 2.2). Carter's windowed attributes may be a vertical window on a single-trace or a lateral window, encompassing multiple traces with the groupings oriented along a picked horizon. Modern seismic interpreters use horizon-based attributes (and extractions) similarly. The primacy of 3D seismic data and volumetric calculations has reduced the application of horizon-based attributes by removing the requirement to interpret seismic horizons explicitly. For example, extracting the mean values of a typical AVO volume (e.g., near minus far or some variant) around a time window of an interpreted horizon takes a certain amount of training and experience to interpret. However, the "mean values… around a time window" of that example needs no explanation to a scientist, technician, or technical manager. For these reasons, a classification system based on these concepts is of little practical use to modern seismic interpreters.

Brown (1996) publishes a notional classification scheme that he later adopts with edits into the fourth edition of Interpretation of Three-Dimensional Seismic Data, which significantly differed from the seismic attribute schemes of Taner et al. (1994) and Carter (1995). Brown's thoughts on attribute groupings came directly from signal processing. Although his approach was methodical, it omits his predecessors' focus on an attribute's interpretational use (Figure 2.3).

In general, Barnes' (1997) bases his "genetic classification" on the concept of the more common term used in data analytics, data lineage, which describes how data relate to or are derived from other data. Barnes proposes using a complex system of attribute divisions (Figure 2.4). These divisions have a possibility of confusing readers by focusing on unmigrated seismic attributes and a less intuitive distinction among 1D, 2D, and 3D seismic attributes; a conclusion we predicate on the assumption that the intended audience of this work is a seismic interpreter. Barnes' (1997) classification is likely intended for seismic processors and interpreters, which makes it less useful for either.

Barnes (1997) further describes attributes as being geologic or geophysical, with the primary distinction being the domain to which the data belong, with depth data being geologic and time data geophysical. The author arrives at this point through (an implicit) logical argument that is simple to understand, yet may not accurately represent the mental model of modern seismic interpreters. Moreover, Barnes (1997) conflates the preexisting ideas of the author's contemporaries to arrive at the presented taxonomy. Although Taner et al. (1994) and Brown (1996) attempt to explain seismic attributes knowing the importance of the emerging quantitative seismic interpretation discipline and the now classic texts describing seismic stratigraphy, Barnes (1997) is more mathematical despite referencing Payton's Memoir 26 (1977). Later, Barnes (2016) addresses these shortcomings with a rewrite of this taxonomy.

The quantitative attribute period (c. 1997–2020)

The quantitative attribute period saw not only the introduction of an increasing number of attributes that measured the seismic response to faults, folds, and thin-bed detection, including coherence, curvature, and spectral decomposition, but it also improved the means to integrate attributes with well control and with each other. Because of technological advances, common practices expanded to include the corendering of two or three attributes u sing red, green, blue (RGB); cyan, magenta, and yellow (CMY); hue, saturation, and value (HSV); and hue, saturation, and lightness (HSL) color models. Coupled scatterplots, opacity, and value thresholds provided an improved delineation of a collection of characteristics that allowed for the segmentation of an otherwise continuous area or volume, commonly called a "geobody." Scatterplots also provided a more quantitative integration of well control, beginning with density and velocity logs for AVO and prestack inversion and later to correlate fractures in image logs to coherence and curvature.

Beginning with Chen and Sidney's (1997a work, researchers in seismic attributes placed a larger emphasis on direct hydrocarbon indicators and their analysis, extending the taxonomies of Taner et al. (1994) and Brown (1996). Chen and Sidney (1997a, 1997b) publish their classification in two installments and are the first to suggest using multiple schemes to describe the same seismic attributes. This novel component is inherently useful to people who have differing mental models or backgrounds. They base their first taxonomy on wave kinematics and dynamics and emphasize signal properties. They base their second taxonomy on reservoir features and focus on attribute usage (Figure 2.5).

Taner (2001) (Figure 2.6) extends the earlier Taner et al. (1994) taxonomy, includes prestack seismic attributes, and adds additional categories of poststack attributes to the original two (physical and geometric) resulting in prestack (e.g., AVO), instantaneous (e.g., Taner et al., 1979), wavelet (e.g., Bodine, 1984), physical (e.g., envelope, frequency, and velocities), geometric (e.g., semblance, dip, and curvature), reflective (e.g., AVO), and transmissive attribute groupings (e.g., average velocity, absorption, and Q).

Taner defines two new terms: primitive and hybrid attributes in which primitive attributes are concerned with discrete calculations and hybrid attributes as composed of combinations of primitive attributes, Taner's example includes hybrid attributes based on artificial neural networks (ANN) — what de Rooij and Tingdahl (2003) call a meta-attribute; however, a more common example is sweetness, which is the ratio between the instantaneous amplitude (amplitude envelope) and the square root of the instantaneous frequency. This novel approach provides insight to the mathematically orientated, but the definitions of "primitive" and "hybrid" are lacking in the original publication because the author does not provide a sufficient number of specific examples.

Liner et al. (2004) describe two broad categories of seismic attributes: general and special. Readers should not conflate the prior discussion on primitive and hybrid attributes with these two categories. Liner defines general attributes as those whose use can be predetermined prior to the context of a specific basin, whereas special attributes are those whose interpretation depends on the context of the specific geologic basin. Liner et al. (2004) also use the concept of "robustness" of an attribute to further highlight their general attribute definition. The term “robust” as used here brings up significant philosophical questions in science, where authors use robust as either an intuitive and imprecise synonym of “reliable,” “trustworthy,” or “credible,” or as “remaining invariant under a multiplicity of independent derivations” (Soler et al., 2012). Liner et al. (2004) use robust regarding all “general attributes,” and by extension the new attribute defined in their work, spectral imaging of correlative events (SPICE) (Smythe et al., 2004), as the former while using the example of AVO with robust applied with the latter definition. It is important to note that the context of this article is Liner et al. (2004) presenting a patented seismic attribute based on the Hölder condition called SPICE. The divisions of general and special, as presented, highlight the importance of general attributes considerably, and the authors describe their newly patented attribute as a significant general attribute. Liner (2016) represents this seismic attribute taxonomy in his later work, where the author altered the terminology from “special” to “local” (Figure 2.7).

Randen and Sønneland (2005) focus on stratigraphic boundaries and their internal configuration in sedimentary systems. Like Liner et al. (2004), Randen and Sønneland (2005) use robustness as a criterion for an attributes inclusion in their work, where the authors use robust as either an intuitive and imprecise synonym of reliable, trustworthy, or credible. Randen and Sønneland (2005) define an implicit classification system that divides the attributes into six explicit categories: 1D attribute calculations (e.g., Taner et al., 1979), dip and azimuth (e.g., gradient vector estimation or covariance estimation), stratigraphic texture (e.g., chaos, filter banks, and divergence), terminations (based on stratigraphic texture attributes), discontinuities and faults (e.g., fault edge, chaos, and variance), and (data) conditioning (e.g., various Gaussian filters).

Because Randen and Sønneland (2005) use an attribute's robustness as a criterion for inclusion into their scheme, in which "any robust seismic attribute must be able to handle dipping layers […]," the exclusion of an attribute implies that the authors deemed it to lack robustness (i.e., they do not find it useful). This implication, and the incomplete definition of robust, is a significant source of potential bias owing to the lack of clarity or objective criteria. It is from this separation of attributes in which the concept of useful and nonuseful attributes first appears. Barnes (2006) popularizes this idea in a later publication. We refer to these concepts collectively as the "uselessness criterion," in which an author defines the uselessness of an attribute using subjective methods that are prone to bias.

Barnes (2016) provides significant edits to his 1997 work discussed previously. He posits the proposal that the community should categorize all seismic attributes by their mathematical, geologic, or geophysical property. Barnes combines two concepts with this definition. The first is that there is usefulness to attributes being grouped by one of three (or several) domains. The second is that interpreters with different backgrounds, and therefore different biases, use seismic attributes in different ways. We refer to "domains" later in this text, of which we define three, "signal property," "mathematical formulation," and "interpretive value," and readers should not confuse our domains with Barnes' "mathematical," "geophysical," and "geologic" categories (Figure 2.8). Where we envision that all attributes exist in each domain. Barnes assigns each attribute to only one. Barnes (2016) references some prestack attributes under the "lithology" title in the presented taxonomy. The author does not discuss them further because they are outside of the stated scope of his handbook.

Marfurt's (2018) attribute taxonomy removes all seismic attributes whose use he finds to have little or no value. He fails to provide an argument for this conclusion beyond citing the uselessness criterion discussed previously. Marfurt provides seven categories: reflector configuration, texture, discontinuity, spectral, impedance, anisotropy, and time-lapse attributes.

The author discards the long-held notion that prestack and poststack attributes are inherently different and distinct enough to serve as a primary division, a distinction that serves as a point of confusion as prestack (postmigration) attribute calculations become more common (Chopra and Marfurt, 2019). Marfurt includes 4D attributes and merges horizon and volumetric attributes (i.e., including time structure in the reflector configuration category). Rightly or wrongly, he considers any seismic processing product, ranging from prestack inversion, to azimuthal anisotropy, to diffraction imaging, that was at the end integrated by an interpreter to be an attribute. However, Marfurt's handling of diffraction imaging and AVO may serve as points of confusion. Specifically, when Marfurt discusses diffraction imaging, the attribute may be a diffraction amplitude or diffraction image volume (Klokov and Fomel, 2012), or it may be another attribute based on that process (e.g., diffraction semblance). Diffraction data begin with a specific set of processing steps that are more akin to another seismic imaging technique, upon which a seismic interpreter may calculate attributes. Marfurt combines multiple concepts, similar to Barnes (2016), to simplify the presented table; however, simplifying the presentation may not be as critical as one may initially assume (based on the collected citation data discussed in the "Historical Usage" section of this paper). The combination of AVO attributes and (presumably) poststack acoustic impedance provides a similar point of confusion for the sake of simplicity.

The artificial and expert systems period (c. 2020 onward)

To understand artificial and expert systems, we begin with the following definitions, which also introduce the high-level evolution of the topic:

1. Artificial general intelligence (AGI) or "strong" artificial intelligence (AI) is an artificial system that has the capability to solve a general task through its ability to understand or learn (Goertzel and Pennachin, 2007). Such a system does not currently exist.
2. "Weak" AI is an artificial system that can function similar to a portion of a mind, but it cannot solve a general task (Goertzel and Pennachin, 2007). Such a system also does not currently exist.
3. "Narrow" AI (often confused with weak AI) is a system that provides a superficial lookalike feature to solve a narrow, predefined set of problems (Goertzel and Pennachin, 2007). Virtually, all AI systems commonly used today are narrow AI (e.g., Siri, Cortana, Alexa, and Google Assistant).
4. Expert systems are computer systems that emulate a human expert's decision-making ability (Goertzel and Pennachin, 2007). These systems were successful forms of AI developed in the 1970s and 1980s, but they suffered from a knowledge acquisition problem — experts by definition are a highly valued, but scarce resource, which presents obvious

problems when training a computer-based on their knowledge. Some industries still use these systems, but the seismic interpretation research focus has shifted largely to more recent AI systems.

5. Machine learning (ML) is a system that can perform a specific task without explicitly being programmed for it (Samuel, 1959). Developers may use supervised, unsupervised, or reinforcement learning-based ML approaches to their systems. Commonly, we place dimensionality reduction in this category; however, it is distinctly different and not directly related to the field of AI inherently.
6. ANN is a system composed of interconnected units, which loosely model the neurons in a biological brain (Goertzel and Pennachin, 2007). The development of AI has rendered this term nondescriptive because most modern AI approaches are ANN.
7. "Deep" learning is a family of ANN in which many layers are used, which can, in theory, be infinite. Business marketers have used the term "deep learning" in so many contexts that the term is no longer descriptive. Early deep-learning networks had as few as three hidden layers and "very deep" networks had more than 16 (Hinton et al., 2006; Simonyan and Zisserman, 2014).

The artificial and expert systems period begins with the increased focus of research and business on narrow AI, represented by the work of Meldahl et al. (2001) and their chimney cube. Although seismic interpreters have leveraged unsupervised approaches (especially in the form of self-organizing maps (SOMs) and feedforward neural networks) since the early 2000s (Taner, 1997; Todorov et al., 1997; Hampson et al., 2000), modern advances in narrow AI propelled this topic forward from the failed attempts of AGI and expert systems of the 1970s–1990s. This period technically began with the popularized defeat of Garry Kasparov (a chess grand master) by IBM's Deep Blue (Hsu, 2004) and continues to the dramatic advances in recent years by Google, Microsoft, and Amazon. Graphics processor units (GPUs), both commercial and bespoke hardware, allowed for the companies' advancements in the areas of computational photography, computer vision, and natural language processing (e.g., Nvidia tensor cores and Google tensor processing units) (Jouppi et al., 2017; Markidis et al., 2018). Further, these specific advancements highlight the potential use of seismic attributes based on narrow AI systems to aid the practice of seismic interpretation.

For several years, professional seismic interpreters have used interactive scatterplots and color blending to combine multiple seismic attributes to arrive at a specific geologic interpretation; however, these approaches typically only manifest themselves as approaches with two or three attributes. There is, overall, a need to use more of our data than a person can conceivably accomplish even using modern workstation approaches. Using dimensionality reduction, unsupervised classification, or ML approaches, provides a means to analyze more than three attributes at the same time.

Our goal is to construct a seismic attribute organization scheme specifically created to enhance the understanding of seismic attributes across data analysis domains and an interpreter's use of attributes in multiattribute or ML contexts. We hypothesize that our communication framework is also adaptable for any future advances in AI or seismic attribute analysis.

Data Analysis Domains

Recall that seismic data fundamentally represent a time series — a series of discrete data sampled over time. Methods of analyzing these data are often used in exploratory data analysis (EDA) or confirmatory data analysis (CDA). In seismic interpretation, EDA techniques rely heavily on qualitative visual methods centered on developing a hypothesis based on observations and statistical inferences. We (seismic interpreters) base these on empirical evidence. CDA techniques seek to develop hypotheses based on quantifiable agreement and deviation from a model. For example, geoscientists who use a priori knowledge of depositional environments to interpret patterns in seismic data are using EDA techniques. Using predictions from calculations outside of the seismic data as a point of comparison and the basis for identifying anomalies in the data (i.e., deviations from the model) are using CDA techniques. Both examples bias the interpretation, one hopes correctly; however, a correct bias is only the case with either luck or by considering all reasonable possibilities.

Professional seismic interpreters who are more conceptual often favor EDA techniques, and they may find themselves in roles described as “general seismic interpreters.” Those who are more mathematical or quantitative often favor CDA techniques, and they may find themselves in roles described as “quantitative seismic interpreters.” Owing to the necessity of addressing those interpreters who fall between these two extremes, researchers in the seismic attribute specialty have developed the various organizational approaches that we have previously discussed.

Without question, those who favor EDA approaches need techniques to highlight seismic data visually or to interrogate their data otherwise quickly — allowing them to find meaningful patterns. These individuals are more geologically minded; therefore, their concerns are primarily geologic pattern recognition. We can split those interpreters who favor CDA techniques into those who favor conceptual models based on algorithmic details or mathematics and those who favor conceptual models based on signal properties of a time series. Both CDA groups understand the subsurface through their knowledge and experience derived from theory or conceptual models.

Neither of these approaches is inherently superior; however, a geoscientist's specific history and background inform their current understandings and approaches through their various biases. Because the central (often unstated) point of grouping anything together is to foster more efficient communication, it is critical that we recognize these three communication paths as extremes with most interpreters preferring some mixture of approaches. From this perspective, we present the prior methods of seismic attribute taxonomy into one of seven data analysis or conceptual domains: signal property, mathematical formulation, interpretive value, and four obvious mixtures of the three.

Historical Taxonomy Usage

Method

We gained the raw citation data for the classification schemes, assigning each citing work a value that we call a citation factor (CF). We found that computer-based assignment was difficult owing to the inability of a computer to understand the specific context. Therefore, we assigned the CFs by hand to maximize accuracy. The potential for human error remains; we attempted to mitigate this error by relying on a single person to ascribe all CFs for consistency. Following a reading of each article for context, we assigned a CF based on the following criteria:

1. Citation factor 1 (CF1) contains the taxonomy in question in the reference list; however, the author did not cite or reference work in the text's body.
2. Citation factor 2 (CF2) references the article in question along with several others in a list reinforcing a particular assertion or statement.
3. Citation factor 3 (CF3) references the article in question by itself, refers to a unique thought or short quote.
4. Citation factor 4 (CF4) references the article in question by itself, refers to a long thought, definition, or significant quote.
5. Citation factor 5 (CF5) references the article in question; however, it expounds on the original idea or quote to derive new meaning or implied meaning in the original.

We do not intend for the CF score to reflect the quality of the original work, the work referencing the original, or the validity of the statements referenced; rather, the CF measures how authors are using preexisting work.

A CF1 shows that the author may have neglected to take out a reference that they no longer needed or they included it for additional reading. In either case, we interpret this event as the author believing that the referenced work may have been an important, related work; however, the author did not find it significant enough to reference in the text. A CF2 implies that the referenced work increases the validity of a statement in a chorus of work; however, it implies that the referenced ideas are not unique to the work being referenced. A CF3 means that a referenced work provides a unique idea or perspective; however, it does not warrant the devotion of significant time to discuss. An author implicitly states the relative importance of a referenced work by spending a significant amount of time discussing it (CF4) or expounding significantly (CF5).

Citation Analysis

Beginning with a list of more than 2100 citing works or "raw data," we manually read each for understanding and context. A significant number of these cited entire books. We omitted any citing work whose context referred to the content outside of the seismic attribute classification. The remaining 287 independent works or "pertinent data" represent a wide swath of geoscience journals and dissertations in Spanish, Polish, French, English, Arabic, and Mandarin Chinese. As of this writing, there are approximately another 200 articles that require translation from Mandarin Chinese. We used automated translation assisted by native speakers when needed.

Where we saw large numbers of citations from any region commenting on or using a particular classification scheme, other regions mirrored that trend. This led us to conclude that the data are free from a regional bias. We analyzed the data for a temporal bias, and we noticed a nonlinear correlation of the number of citations to the time since publication. We hypothesized that such a correlation would exist owing to the competing factors of the time since publication and the perceived influence of the work. It is obvious from the data that any publication more than eight years old (and possibly more than two years old) has been in circulation long enough to judge the usefulness and impact. The comparison of the number of citations to work of a similar age reflects this hypothesis. We expected more recent works (less than two years since publication) that lack citations and limit our ability to assess the relative impact, significance, or usefulness accurately. We noticed this effect in our study.

Prior seismic attribute taxonomies do not reflect the full extent of the seven data analysis domain categories discussed in the previous section because there does not exist a seismic attribute taxonomy that reflects a mixture of the discussed domains. Therefore, we grouped each taxonomy into the remaining six categories (Figure 2.9), and we did the same with the respective citations (Figure 2.10). Additional factors such as the age of the publication, when the authors' published books or if/when authors published updates do not have any significant impact on this observed preference by the geoscience community.

In order for the usage patterns to stabilize, a work should have between 25 and 50 citing works. Going back to our subjective scale of CF1-CF5 (as discussed previously), we hypothesize that a system becomes more accepted or mainstream when the relative number of citing works with lower CFs would increase as compared to the next higher CF. This would occur because the most interested researchers investigate new ideas, define norms, and establish levels of acceptance. As the acceptance grows, the more casual researchers will use those ideas as they focus on other related areas in which they are most interested (Figure 2.9). The ratio of the most interested researchers (our > CF3 category) to the casual researchers (<CF3 category) should reach a maximum and decline as the time after publication increases. By this standard, the "interpretive" and "signal and interpretive" classifications are the most mainstream, the

“signal properties” and “mathematical formulation and interpretive” taxonomies are less so (Figure 2.10). The remaining conceptual domains lack enough citing works for us to identify a stable usage trend. Figures 2.11 and 2.12 show the CFs over time for the interpretive value and the “interpretive and signal” conceptual domains, which illustrate these trends. A close inspection of Figure 2.11 shows that the low-CF (<CF3) occurrences happen first; however, this observation is because of the details of the citing works. Although the first citation for Taner et al. (1994) is indeed a low-CF citation, there are six works that do not properly cite Taner et al. (1994), and we identified them as a CF1 (Walls et al., 1999, 2000, 2002; Taner et al., 2001, 2002; Taner, 2002). Had these authors correctly cited their referenced work, the citing works would have been greater than or equal to a CF3.

Note the crossover of the signal properties and the interpretive conceptual domains in the cumulative citation count chart (Figure 2.12). As Figure 2.9 illustrates, the usage trend for the signal properties and the signal and interpretive conceptual domains is fairly similar for high CFs (>CF3). The interpretive conceptual domain lags significantly. In fact, this group’s usage pattern for the signal property conceptual domain outpaces that of the interpretive value until a crossover at 22 years postpublication. We identify the culprit for the crossover from Figure 2.13 in Figure 2.14, which illustrates that usage among more casual researchers (<CF3) never developed for the signal property taxonomies; however, it has seen larger relative use by those most interested in this area of geophysics. We hypothesize that the identified crossover occurred partly or wholly because the author of the sole signal property taxonomy only did so in an initial nonpeer reviewed magazine (Brown, 1996) and in a

fully developed version in his book (Brown, 2011), which limited the audience for the work.

Creating Useful Seismic Attribute Taxonomies

In this section, we present our view on seismic attribute classification. We informed our view through the understanding and critical analysis of the most significant preexisting seismic attribute classification schemes and the works that reference those schemes. We submit three classification taxonomies that correspond to the three data analysis domains discussed in the “Data analysis domains” section of this work, which are the signal property, mathematical, and interpretive value data analysis domains. We accompany the three taxonomies with a cross-referenced chart that illustrates the attributes we use across the data analysis domains, and we provide a basic definition of each attribute in this paper to aid readers’ understanding and rationale behind our design choices. These components represent a unified communication framework upon which any group of seismic attribute researchers or professionals can communicate, make quicker observations, and disseminate new lessons by sharing a common language across technical backgrounds.

By using the included charts and definitions, a seismic interpreter may place any seismic attribute that we have overlooked as well as any new attribute into our framework. We designed our communication framework to be adaptable so that scientists can easily alter it to accommodate their preferred attribute algorithms. We promote this philosophy because no significant body of work exists that conclusively demonstrates the efficacy of one attribute over others that perform similar functions, that argues in favor of (and under what conditions) an interpreter should use multiple similar attributes (if at all), or the impact of similar attributes on ML-type systems.

Design Choices

Inherently, we made multiple design decisions when we designed our seismic attribute taxonomies. We based these choices on our background, experience, and preference. This section details those choices and their rationale.

Terminology

In this work, we have used the terms “classification,” “classification scheme,” “organization,” “taxonomy,” and “taxonomic scheme” as synonyms. Although it may be possible for a skilled grammarian to parse these terms and ascribe subtle differences, we use them interchangeably.

We use the term “node” when referring to our diagrams. A node is a component of our diagrams with an outlined container surrounding it. Nodes represent mental subdivisions but not attribute products directly, which we show without a surrounding container.

Augmented seismic attributes specifically require a posteriori information; examples include attribute calculations made on horizons directly (a common practice with geometric attributes historically) or model-based seismic inversions. We omit supervised classification methods that require input independent of the data (i.e., training data from data set “A” and applied to data set “B”) in this definition.

On the Signal Property Domain

General — When discussing the analysis of signals, it is probably the most straight-forward to discuss the various signal’s properties, namely, the amplitude, phase, and frequency. We begin with a central node labeled “seismic data,” which in this context is postmigration; however, this distinction refers to a typical application rather than an inherent limitation. We chose a hierarchical structure visualizing parent-descendant relation among the example attributes. We let the need to represent this complex structure on a single page drive the overall layout in which the central node extends outward in all directions rather than in a single direction only.

From this node, we have two major divisions. By using a variable division, we account for processes that have become significantly more important in modern workflows. Specifically, computer-based classification methods or AI-derived attributes, as those become available. The variable branches do not directly relate to any part of the seismic signal inherently and are input dependent. The basic components of a signal are amplitude (or magnitude), phase, and frequency. Attenuation is not a component of a signal; it is what can occur to a signal over time.

Visual effects — We color-coded this diagram, such that mixing the three components (amplitude, phase, and frequency), that we represent by blue, green, and red, results in the mixture of the component colors as one would expect (i.e., yellow [amplitude and frequency], magenta [phase and frequency], or white, represented as gray [amplitude, phase, and frequency]). Dark gray is used to identify the processes whose signal property depends on input. Finally, we indicate the degree that an attribute lies from the originating node by the line thickness such that the thickness is inversely proportional to the distance.

On the Mathematical Formulation Domain

Although our opinion is that the signal property and interpretive value diagrams are the most useful and important, one should understand the general mathematics behind the common attribute families. Others conceivably could add other divisions; however, we attempted to be complete without overwhelming the reader with superfluous detail. Strictly, “component separation” and “dimensionality reduction” are not direct mathematical operations, the intents of the corresponding processes are thus described even though the mathematics are slightly more complex than one operation.

On the Interpretive Value Domain

The interpretive value of an attribute is of paramount importance. It is the reason for any geoscientist to become engaged in seismic attribute analysis at any level. Interpretive value is simultaneously simple for most geoscientists to understand intuitively and difficult to discuss. There are numerous claims, procedures, and case studies that support (and sometimes disprove) using attributes for various interpretive goals. We attempted to provide a general look at this space without judging or validating any particular opinion. The most debated areas are thin-bed analysis and fluid detection, in which some claim the ability to detect acoustic impedance contrasts at or near the reflection coefficient level (Zhang and Castagna, 2011) or reliable partially saturated gas (approximately 10%) in brine. Our opinion on the efficacy of these procedures is irrelevant for this work. Because we have not independently verified any claim, we provide a framework that is broad, and, in our examples, we present multiple attributes that provide value when interpreting multiple geologic or geophysical goals.

On Taxonomy Construction

Provided with the discussed design choices and definitions, the overall layout and placement of seismic attributes within our three seismic attribute taxonomies should be intuitively obvious to most readers. Readers can cross-reference the figures to understand our view of seismic attributes across the defined data analysis domains. As noted (on the interpretive value taxonomy), some attributes are necessarily broad, and we do not show them to enhance readability.

Discussion

Historical Context

In this section, we use the premise that the published literature will serve as a useful proxy to the unavailable data regarding practical seismic interpreters and a representative sample of seismic attribute researchers. Because academic researchers are far more likely to publish than practicing interpreters, it is possible that our sample underrepresents that group. However, our informal professional and academic experience, as well as the experience of several colleagues we consulted throughout this work, agree with the observed trends in the data.

The hybrid "interpretive value and signal property" scheme in our analysis is by far the most heavily used in the publication record. Further, the only "mainstream" (as we previously defined the term) taxonomies are those from the interpretive value, signal property, and interpretive value and signal property data analysis domains. It is clear that authors who need a practical reference favor Chen and Sidney (1997b). Many seismic attribute researchers (who do not need a practical reference) develop and promote their own attribute taxonomy according to their perspective, which is often not useful to the practical seismic interpreter (as illustrated via the citation record).

It is apparent that the authors of citing papers often do not carefully and critically read the contents of Chen and Sidney (1997a, 1997b), the most favored seismic attribute taxonomy in the literature, which we infer through the highly inaccurate estimations of seismic attributes described in those taxonomies, which range from more than 60 to 224 to “literally hundreds” or “hundreds” (Odegard et al., 1998; Saggaf et al., 2000; Liner et al., 2004; Costa et al., 2007; Liner, 2016; Roden and Chen, 2017; Tayyab et al., 2017) when referencing Chen and Sidney (1997a, 1997b). See Figure 2.15 for a visual depiction colored by publication type.

The important point is not the inaccurate counts; it is the inference that those counts and the specific attributes shown are irrelevant. Otherwise, researchers would not use the Chen and Sidney (1997a, 1997b) scheme because the attributes described therein are largely historical and out of date with modern workflows. What seems important is the rhetorical argument afforded by a classification scheme that discusses concepts across the backgrounds of interpreters and researchers (the data analysis or conceptual domain) and the implied authority that accompanies the presentation of the 63 seismic attributes. Readers understood Chen and Sidney’s general argument and how other (unreferenced) attributes fit into that framework through their examples. However useful Chen and Sidney (1997a, 1997b) has been, it becomes increasingly more difficult to use as an effective communication tool as time passes.

Although the mathematical, “mathematical formulation and interpretive value,” and “mathematical formulation and signal property” systems fail to achieve our definition of mainstream, we do not recommend the wholesale dismissal of mathematical systems. Because multiattribute analysis techniques become more commonly used, it is our judgment that the importance of mathematical independence is of critical importance. Unfortunately, an improper application of the Barnes' uselessness criterion (Barnes, 2007) affects these systems as presented by the original authors. Instead of developing a method to remove attributes and create a subset of algorithms to use, they rely on personal judgment. When personal judgment is a major factor, there is a higher likelihood of bias that limits one's work and its overall usefulness, which is true even when interpreters are defining which attributes to exclude for their work. Although Barnes never advocated for a specific attribute set in his 2007 paper, there are no known cases in which researchers systematically argue against the attributes they ignore or for attributes they do not. The result of the uselessness criterion applied thusly is a fractured community of researchers and a disconnect between professional practitioners and subject matter experts (SMEs).

Marfurt (2018) is the most recent to provide a list of usable seismic attributes. The author begins by listing attribute classification schemes, citing the use of the uselessness criterion and stating, "obviously, I will avoid including any useless attributes in this book." Then, the author proceeds to have sections of duplicate attributes that would fail the uselessness criterion (e.g., curvature shapes, curvature at differing wavelengths, and discontinuity). Although an SME will have no significant issue navigating texts such as this, such texts leave the less specialized reader with the potential misunderstanding of what constitutes a useless attribute and when, if ever, to apply seemingly similar attributes. We highlight Marfurt (2018) specifically because it is the most recent material on the subject, and it should represent a sample of the most up-to-date thinking on the topic. However, what is missing is why the author omitted the “useless attributes” (Marfurt, 2018), with which many practitioners are familiar. Most seismic interpreters lack many of the attributes that the author mentions in this and so many other texts by other researchers. In the end, arguing why a practitioner should omit something and replace it with other approaches is often just as important as why the proposed approach works at all (Kim et al., 2019).

Taxonomy Usage

To use an attribute in a workflow, one must understand as much about the attribute as possible. Failure to do so may result with unintentional inclusion (or exclusion) of duplicate information in multiattribute analysis, failure to make critical observations that the attribute may highlight, or the overinterpretation of a seismic attribute (prompting spurious correlations) (Kalkomey, 1997). Often, geoscientists consult a seismic attribute matrix to aid in their understanding and to define appropriate usage; however, the vast majority of such matrices we have reviewed have either an author’s unsupported bias or an overinclusive nature (i.e., the authors present the usefulness for many attributes for so many purposes that the decision to use one attribute over another is arbitrary). Examples are the dGB’s OpendTect Attribute Matrix (no longer online and replaced with the similar yet different OpendTect Attribute Table), Geophysical Insights’ Attribute Usage table, Schlumberger’s untitled attribute use table, and Landmark’s (Halliburton’s) usage guidelines within their PostStack reference manual.

Researchers have correctly identified the inability of authors (either individual researchers or software vendors) to provide clear guidance on the actual usefulness of so many seismic attributes (Randen and Sønneland, 2005; Barnes, 2006). We refer to this as the uselessness criterion; works such as Pigott et al. (2013) specifically attempt to apply the uselessness criterion via real data examples and careful analysis. However, these works are rare in the literature. The more common approach is to apply the uselessness criterion with a hidden rationale. Historical attributes plague the many commercial software packages because the authors of the software assess the business value of removing outdated functions are, presumably, less than their ongoing maintenance. The result is a complex web of purported uses and antiquated algorithms that are unlikely to produce value to the end users that they, the software vendors, claim to serve. Pigott et al. (2013) exemplify this observation because the authors begin with 50 seismic attributes and identify only eight that provide a meaningful interpretive value for their clastic stratigraphic interpretation.

Fortunately, as we note earlier in this paper, it is clear that the specific attributes mentioned in taxonomies such as ours are not of primary significance. However, the overall framework and the ability to communicate between individuals who understand seismic attributes through different data analysis domains (those being EDA and the two types of CDA) is critical.

Therefore, we see the practical use of Figures 2.16, 2.17, and 2.18 as setting up a shared communication framework that spans the various backgrounds found among seismic interpreters. In these three taxonomies:

1. We provide 37 clear attribute examples for every category, in which readers can understand every attribute example across the data analysis domains.
2. We show the hierarchy or genetic ownership when needed (e.g., moving from dip to curvature to aberrancy), but we do not let this drive the overall organization.
3. We provide color and visual cues to reinforce the organization when appropriate.
4. We envision that readers can easily identify where overlooked attributes, historical and modern, fit into our communication framework, allowing all readers to understand their preferred attribute without the implicit bias that affects other attribute schemes.

Table 1 summarizes our example attributes across all of three of the seismic attribute taxonomies. Table 2 provides a brief definition of each attribute example.

Signal Property Taxonomy

Figure 2.16 represents our seismic attribute taxonomy derived from the seismic signal property. Such a taxonomy is useful to those individuals who favor a perspective based on signal theory and CDA techniques. We view most horizon-derived attributes (i.e., an attribute calculated from the horizon itself) as legacy calculations that have little use in modern attribute workflows. Although useful, neither horizon extractions nor calculations between horizons (i.e., minimum/maximum values, mean values, number of peaks/troughs, etc.) are significantly different enough to require specific mention on an attribute classification system. It is obvious to modern seismic interpreters that these methods are available to understand the underlying attribute values. All calculations that require a priori information are inherently augmented calculations. Such attributes are often useful and encouraged. Classification methods include all AI and ML algorithms as well as any method used to classify an underlying attribute, of which the stacked amplitude is the most common. Supervised methods such as convolutional neural networks (CNN) most commonly use training data derived from a group of seismic volumes or a small portion of the seismic volume that the interpreter wishes to classify. Therefore, we exclude the general form from the "augmented" division. The remainder of the divisions should be self-explanatory to the reader with the possible exception of similarity algorithms to minimize or exclude the effect of amplitude changes (e.g., the energy ratio similarity).

Mathematical Formulation Taxonomy

Figure 2.17 represents our seismic attribute taxonomy derived from the mathematical formulation of each attribute. Interpreters who prefer understanding seismic attributes through their mathematics would prefer this style of organization. In practice, we find that Figure 2.17 is useful to understand the basic mathematical relationship between various seismic attributes.

We grouped spectral decomposition attributes together; however, this group represents many mathematical computations; the most common of which are the short-time Fourier transform, continuous wavelet transform, matching pursuit, and S-transform. The products are related — because they all estimate the components of the same underlying signal. However, the specific mathematics can be significantly different. They are all computed directly from the seismic trace, and interpreters rarely, if ever, use different methods together.

Gray-level cooccurrence matrices (GLCMs), attribute normalizations, and similarity algorithms use statistics or statistical mathematics to generate their products. Like the spectral decomposition attributes, the mathematics are significantly different between them; however, each of these processes compute attribute based on the relationship between a given sample and the neighboring samples in at least one dimension.

Interpretive Value Taxonomy

Figure 2.18 represents our seismic attribute taxonomy centered on the interpretation goal or the value to interpretation that a given attribute offers. This particular organization requires that we list duplicate attributes if an attribute is useful in more than one interpretation goal. Critically, we did not verify the claims that researchers report on seismic attribute usage. This information would be valuable and time-consuming. We identify this work in the "Suggestions for further study" section.

We excluded principal component analysis (PCA), independent component analysis (ICA), SOMs, generative topographic maps (GTMs), and ANN because their use depends on the input attribute, and, because we did not independently verify the usage, providing an interpretive recommendation was beyond the scope of this work. We also excluded horizon geometry attributes because it is obvious where they would fall (under faults and folds).

We highlight the use of color blending in combination with dip, curvature, and aberrancy attributes as well as spectral decomposition. Interpreters commonly pair these attributes with color blending to highlight structural, stratigraphic, or fluid changes. The detection of thin beds is historically a point of contention, and specifically which attributes and how to use them is still the subject of open debate in the literature with a recent review of instantaneous attribute combined with SOMs indicates a dubious correlation (Barnes, 2017). Moreover, when looking at instantaneous attributes in particular, previous works indicate underlying implementation issues, which can cause issues with small-scale interpretations (Adams and Markus, 2013; Xing et al., 2017, 2019).

Conclusion

We have attempted to summarize, analyze, critique, and understand the state of seismic attribute taxonomies or seismic attribute categories and divisions. We believe that such a historical review allows us and our readers to understand researchers', specialists', and day-to-day seismic interpreters' evolution of thought. The community's significant effort spent attempting to simplify, consolidate, or perfect a single attribute classification scheme has yielded a variety of schemes that have provided value to different individuals at different times. However, the current state of the taxonomies is lacking, and the most used taxonomies are woefully out of date. One of the most significant changes to how the geoscience community approaches seismic attribute analysis was the codification of the uselessness criterion. To date, no one has attempted to apply this or an approach that is systematically similar to streamline the state of seismic attributes in any way other than inconsistently and subjectively. It is here where further work remains. It is here where the gulf between novice practitioners and SMEs divides and creates inconsistent language, results, and, ultimately, understanding.

To facilitate communication and update the literature on this topic, we have submitted a seismic attribute communication framework, which presents 35 seismic attributes across the three identified data analysis domains used in this paper. As a critical part of this framework, we have included two charts, one to define the seismic attribute examples that we use and the second to cross-reference the attributes across the data analysis domains. We hope that these charts will aid individuals who use multiple attributes in their interpretation workflows in industry and academia. Readers should be able to easily expand our charts to include new or omitted seismic attributes, which allows others to customize the charts to a particular company's or individual's work practices. We have omitted attributes that are less commonly used, in our experience, from the taxonomy charts. This does not suggest the uselessness of these missing attributes; it underscores our desire to maintain a level of clarity in our presentation.

Suggestions for Further Study

This work began as historical in nature, and, for practical use, we paired it with a seismic attribute communication framework informed by the information contained herein. Overall, the geophysical community lacks a clear understanding regarding seismic attribute usage in modern workflows, and any true best practices are, therefore, impossible to discern. We recommend that the seismic interpretation community conducts a meta-analysis on each attribute to determine the context of use and its overall popularity among professionals and researchers. Unfortunately, these are time-consuming and expensive projects that may have little to no immediate commercial value.

Figures

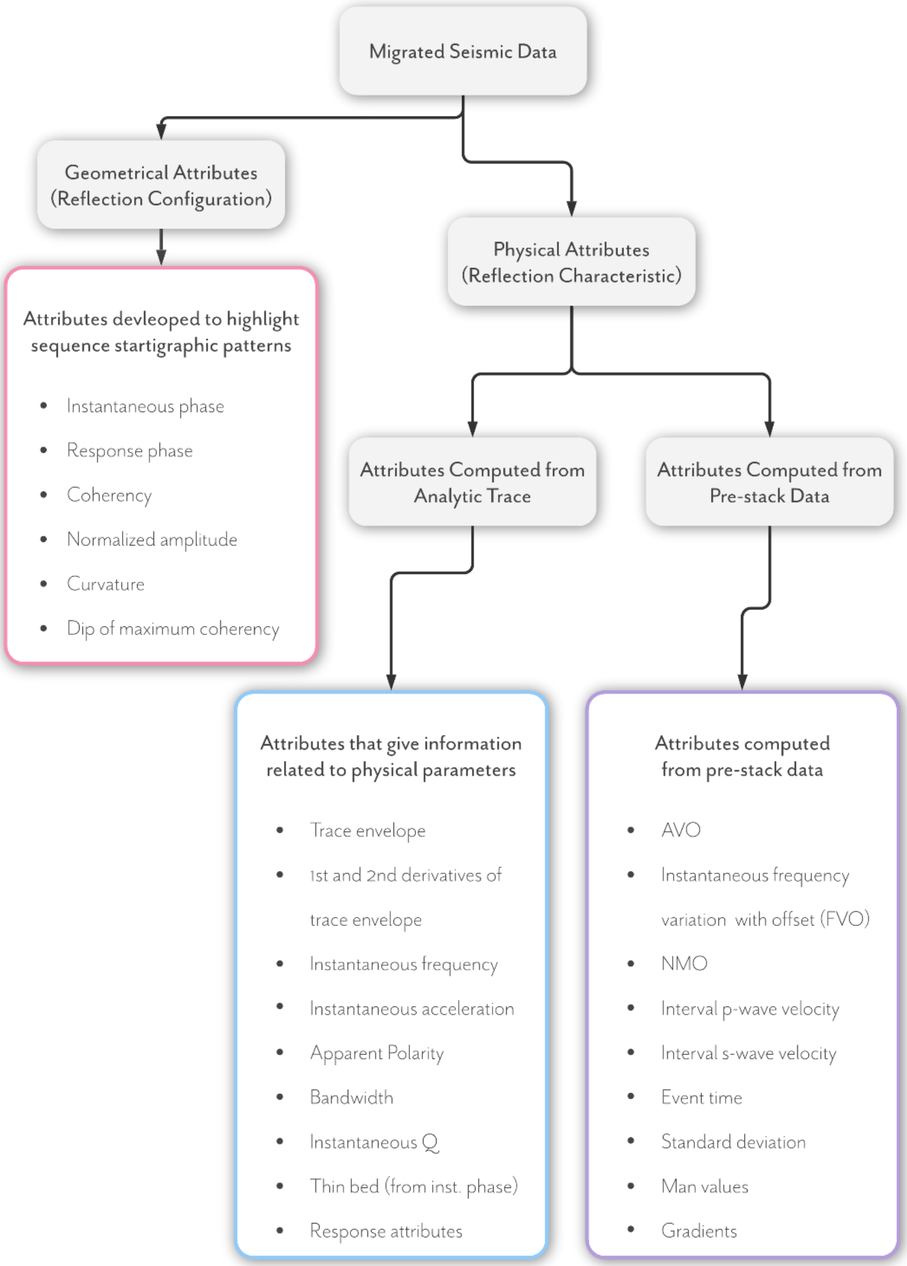


Figure 2.1: Seismic attribute taxonomy after Taner et al. (1994)

A graphical representation of the seismic attribute categories described in the source material, Taner et al. (1994). Seismic attributes categories based on the reflection configuration or reflection characteristics. The authors describe reflection configuration, or geometrical, attributes as useful for structural and stratigraphic interpretation. The authors describe reflection characteristics, or physical, attributes as useful for prediction or extrapolation of lithological or reservoir characteristics.

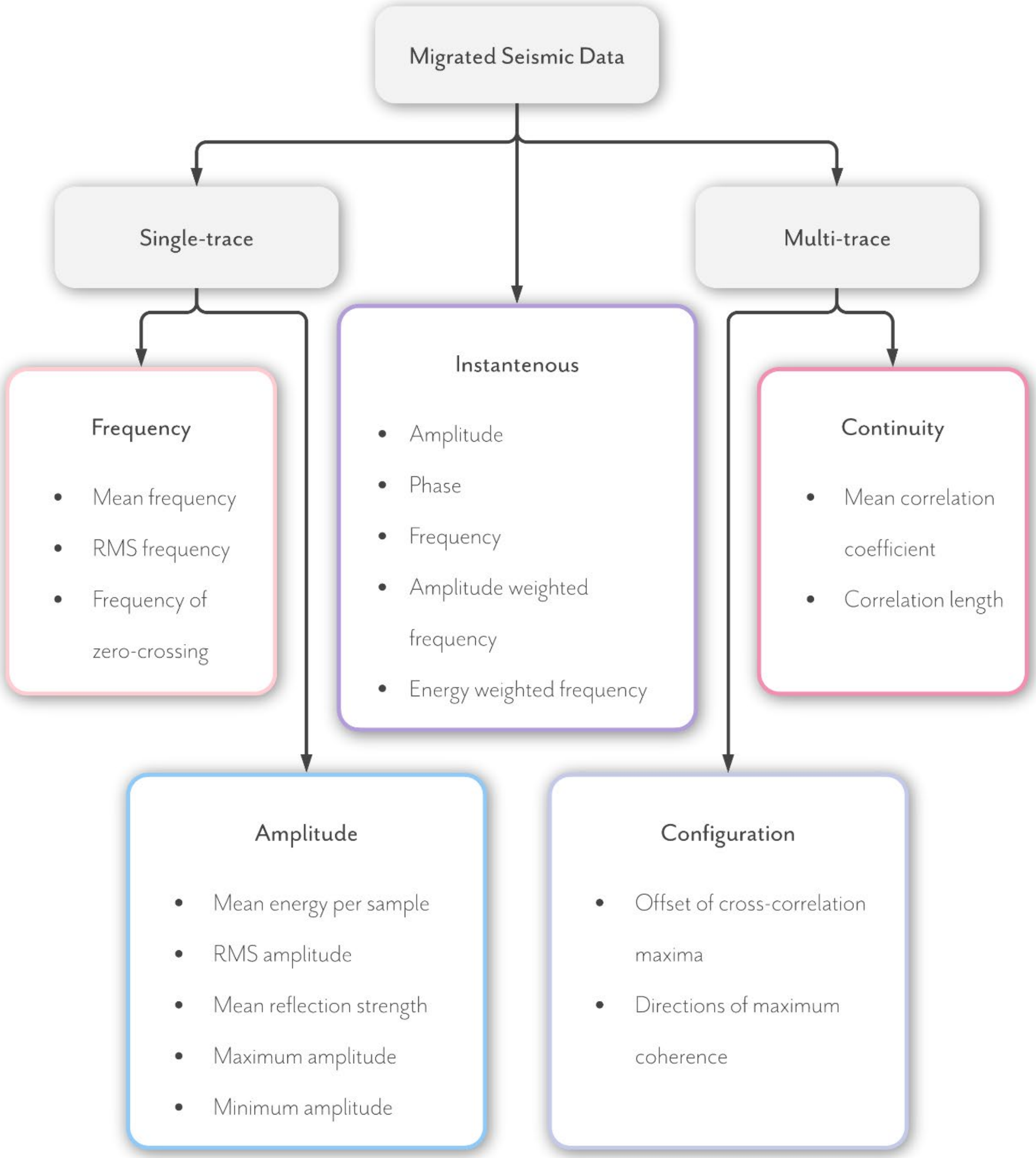
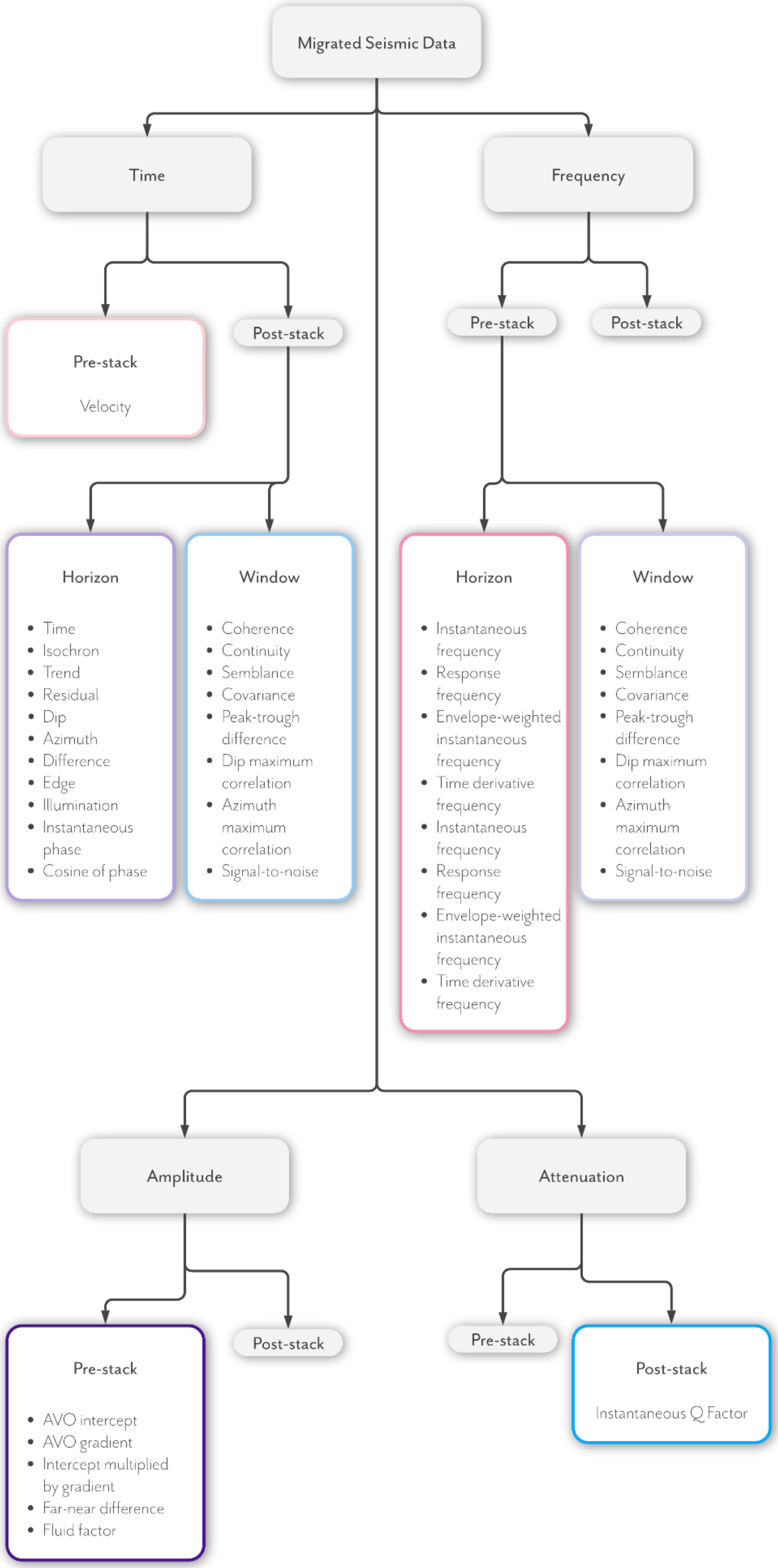


Figure 2.2: Seismic attribute taxonomy after Carter (1995)

A graphical representation of the seismic attribute categories described in the source material, Carter (Carter, 1995). Building on the prior work by Taner et al. (1994), Carter establishes a specific category for instantaneous attributes separate from other single-trace attributes. In doing so, Carter (1995) focuses on the significance of a component of the algorithm. When considering a limited number seismic attributes only such a construct may be useful; however, as researchers develop more attributes, these categories quickly become a less efficient organization method.



Migrated Seismic Data
Time
Frequency
Pre-stack
Velocity
Post-stack
Pre-stack
Post-stack
Horizon
Time
Isochron
Trend
Residual
Dip
Azimuth
Difference
Edge
Illumination
Instantaneous phase
Cosine of phase
Window
Coherence
Continuity
Semblance
Covariance
Peak-trough difference
Dip maximum correlation
Azimuth maximum correlation
Signal-to-noise
Horizon
Instantaneous frequency
Response frequency
Envelope-weighted instantaneous frequency
Time derivative frequency
Instantaneous frequency
Response frequency
Envelope-weighted instantaneous frequency
Time derivative frequency
Window
Coherence
Continuity
Semblance
Covariance
Peak-trough difference
Dip maximum correlation
Azimuth maximum correlation
Signal-to-noise
Amplitude
Attenuation
Pre-stack
AVO intercept
AVO gradient
Intercept multiplied by gradient
Far-near difference
Fluid factor
Post-stack
Pre-stack
Post-stack
Instantaneous Q Factor

Figure 2.3: Attribute taxonomy after Brown (1996) as extended by Brown (2011)

A graphical representation of the seismic attribute categories described in the source material, Brown (2011). By focusing on the signal properties of the seismic waveform, Brown (2011) forces the reader to link the signal properties to useful interpretation goals. In practice, many seismic interpreters lack a signal processing background, and may, therefore, find this requirement less than optimal. Undoubtedly, Brown (2011) intends to totality of the work to speak to this. It is possible that Brown (2011) intended all readers to ground themselves in basic signal theory, which the author later links to seismic interpretation objectives. By a reader taking this small section out of this context of the larger work such a link is severed. Either situation, the requirement that a reader absorb the entire work or that they possess a strong background in signal theory, adds obstacles that appear to hinder adoption by the seismic interpretation community. Importantly, the author presented neither the 1996 version nor the 2011 version in either a peer reviewed context or a conference abstract, a distinction that Brown (2011) shares only with Randen and Sønneland (Randen and Sønneland, 2005), who published in a larger edited work.

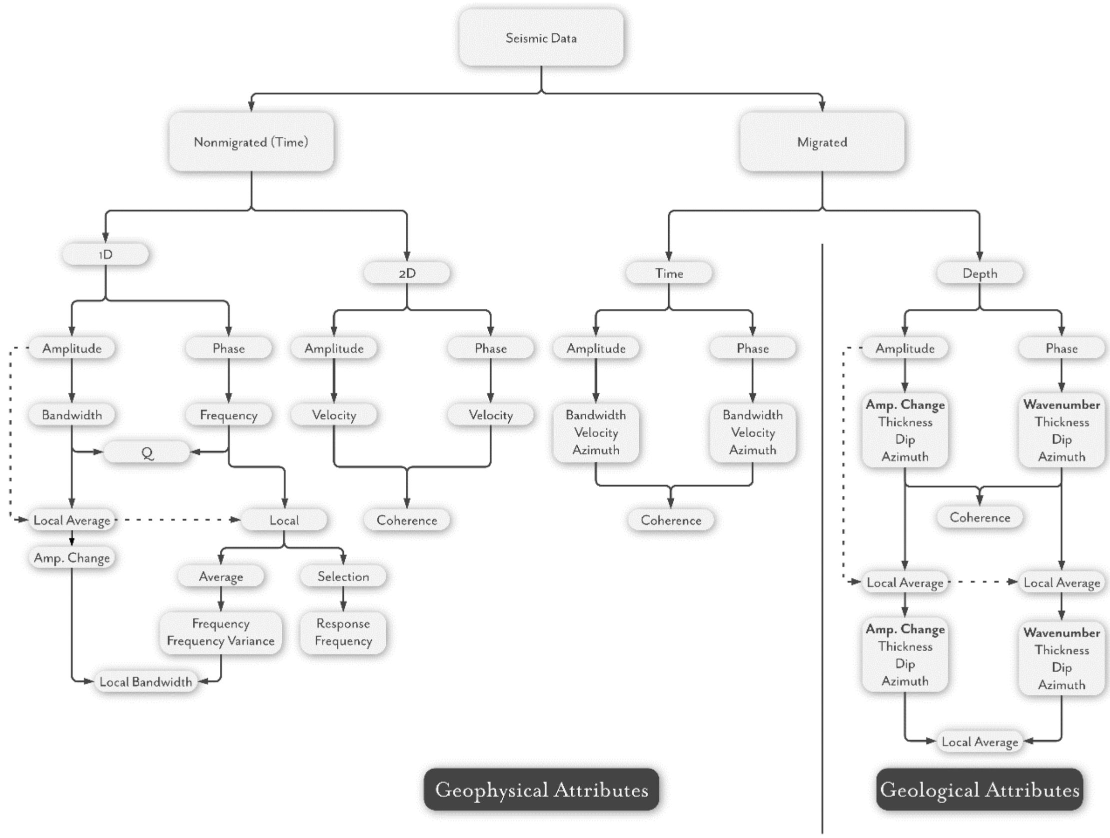


Figure 2.4: Seismic attribute taxonomy after Barnes (1997)

A graphical representation of the seismic attribute categories described in the source material, Barnes (1997). Representing an early concept of grouping seismic attributes based on their data lineage, Barnes (1997) proposes a scheme that we find difficult to update or extend to attributes that the author omitted or that did not exist at the time of publication. The update provided by Barnes (2016), which is essentially a rewrite, is significantly more concise and digestible. Barnes (1997) introduces a division between geophysical and geological attributes based on the data domain (time or depth).

Figure 2.5a: Seismic attribute taxonomy after Chen and Sidney (1997)

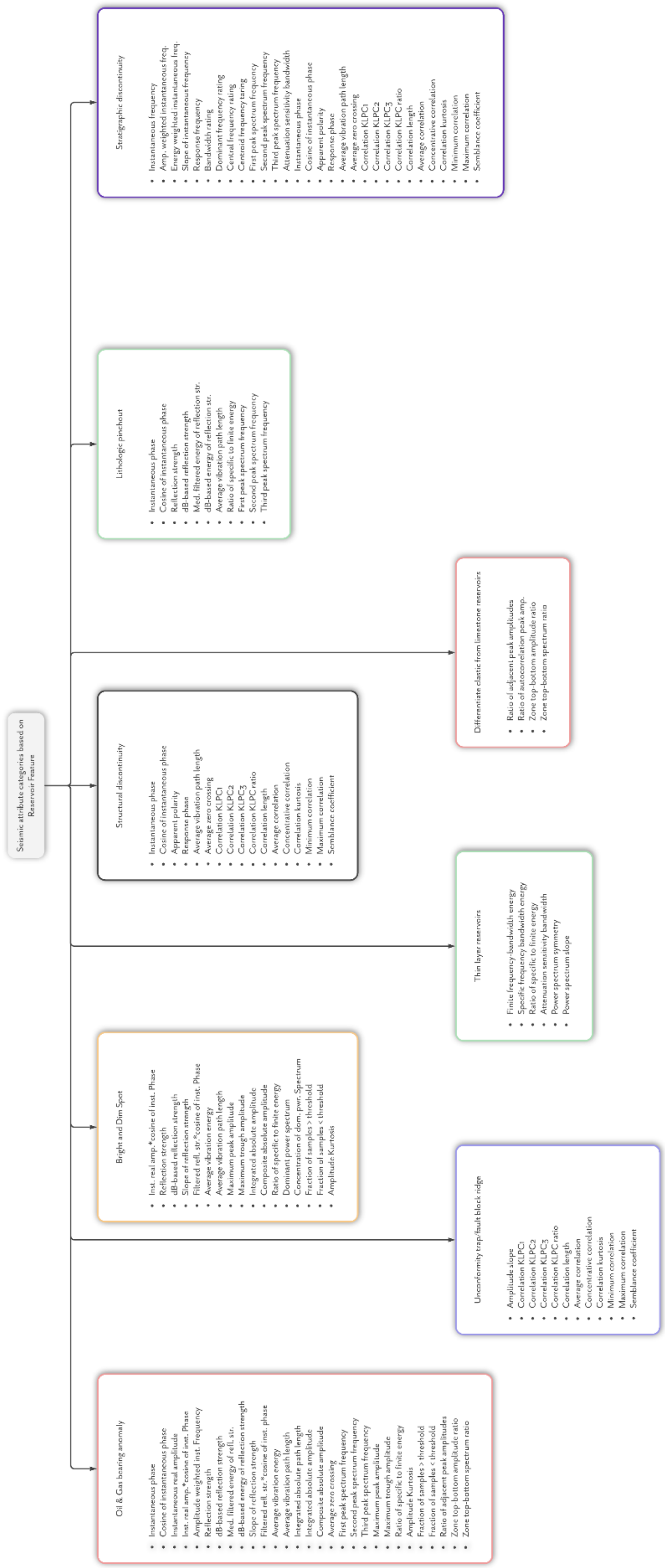


Figure 2.6b: Seismic attribute taxonomy after Chen and Sidney (1997)

Figures 2.5a and 2.5b: Graphical representations of the seismic attribute categories described in the source material, Chen and Sidney (1997). The authors propose two taxonomy schemes based on either the signal properties (described as wave kinematics/dynamics) and interpretive value (described as reservoir feature). By linking the two schemes, the reader can cross-reference the attributes desired for a given interpretive value to understand the portion of the signal they will interrogate (or vice versa). A necessary result, but a point of confusion, is the repetition of attributes in the interpretive value presentation. The author does not discuss if the reservoir feature taxonomy represents their best practices (independently verified) or those reported by colleagues.

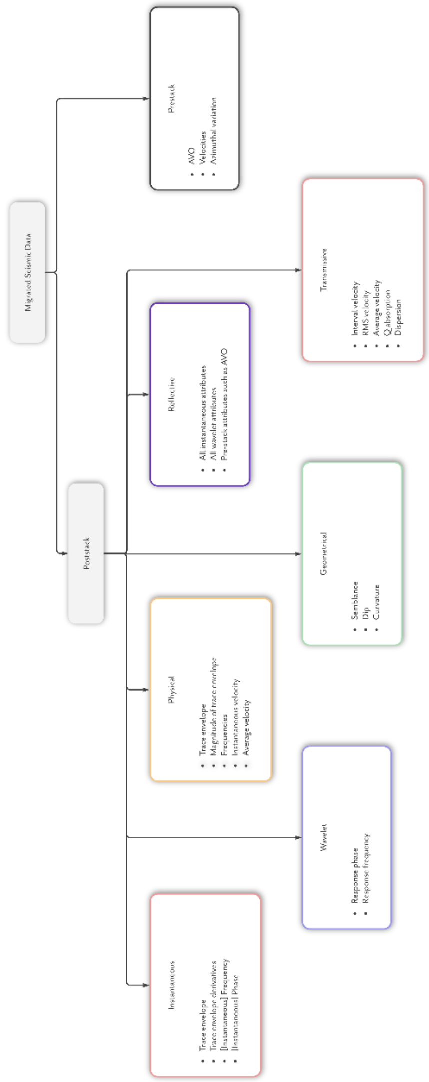


Figure 2.7: Seismic attribute taxonomy after Taner (2001)

A graphical representation of the seismic attribute categories described in the source material, Taner (2001), whose lineage follows from Taner et al. (Taner et al., 1994; Taner, 1999) to Taner (1999), with the intermediate publication being the least significant of the three. Taner (2001) adds many divisions. A strict reading of Taner (2001) provides poststack and prestack attributes. The author subdivides the poststack into instantaneous or wavelet. These two subdivisions are either physical or geometrical, which are further divided with prestack attributes into reflective or transmissive. The first division after poststack is instantaneous or wavelet, where wavelet attributes are themselves a representation of instantaneous attributes (Bodine, 1984). Moreover, the community does not regard geometrical attributes as a category of instantaneous (and never has). Therefore, we provided the examples and divisions in the work as equal-level categories directly below poststack attributes.

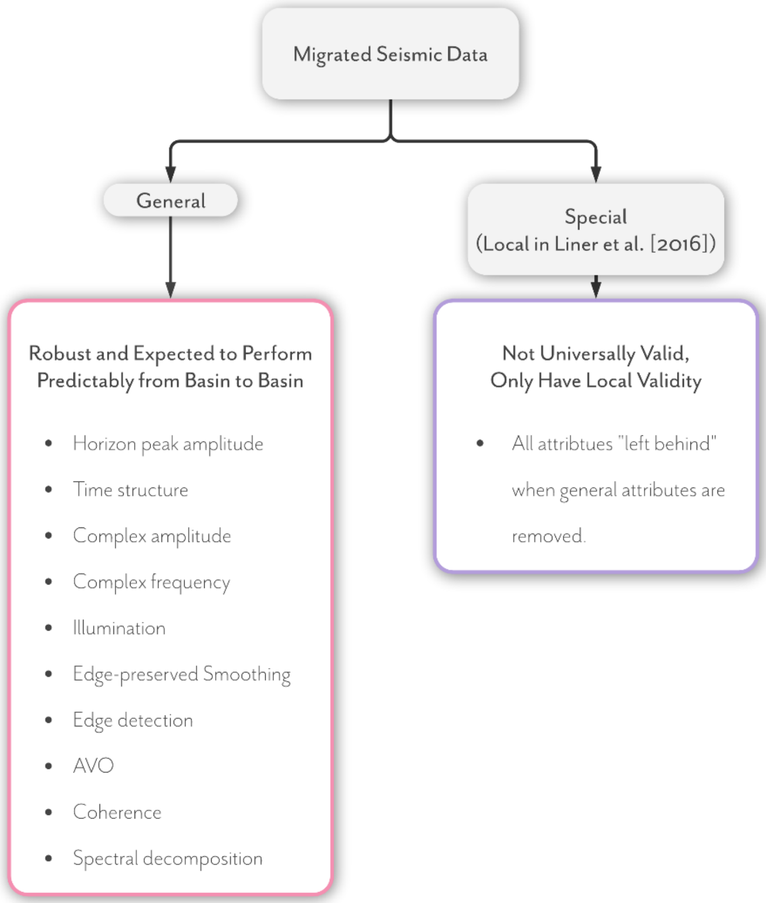


Figure 2.8: Seismic attribute taxonomy after Liner et al. (2004)

A graphical representation of the seismic attribute categories described in the source material, Liner (2004), which the primary author slightly altered in Liner (2016). As a concept, understanding attributes that an interpreter could rely on as basin independent would be significantly useful; however, the authors failed to establish the basis for the members of each attribute category. What the authors consider being "robust and expected to perform predictably from basin to basin" is equally unclear. The authors fail to provide the reader with useful information such as under what processing workflows does this definition holds (i.e., what processing assumptions does the author use in this definition).

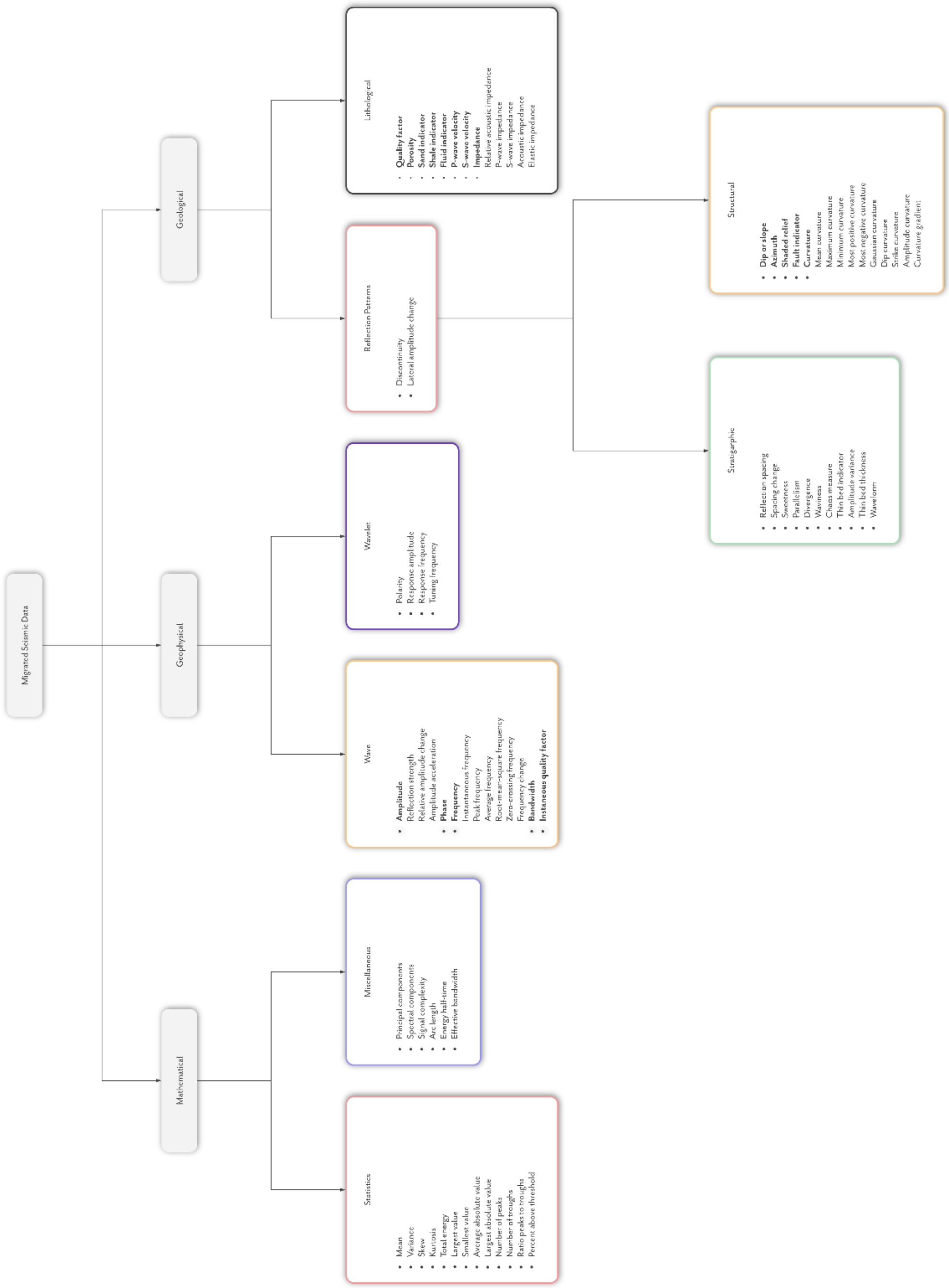


Figure 2.9: Seismic attribute taxonomy after Barnes (2016)

A graphical representation of the seismic attribute categories described in the source material, Barnes (2016). A rewrite based on the earlier work Barnes (1997) placing all attributes in one of three categories: mathematical, geophysical, and geological. Barnes (2016) mixes the concepts we describe at the data analysis (or conceptual) domain, data lineage, and interpretive value; however, the exclusive nature of the application of the interpretive value domain places significantly less emphasis here.

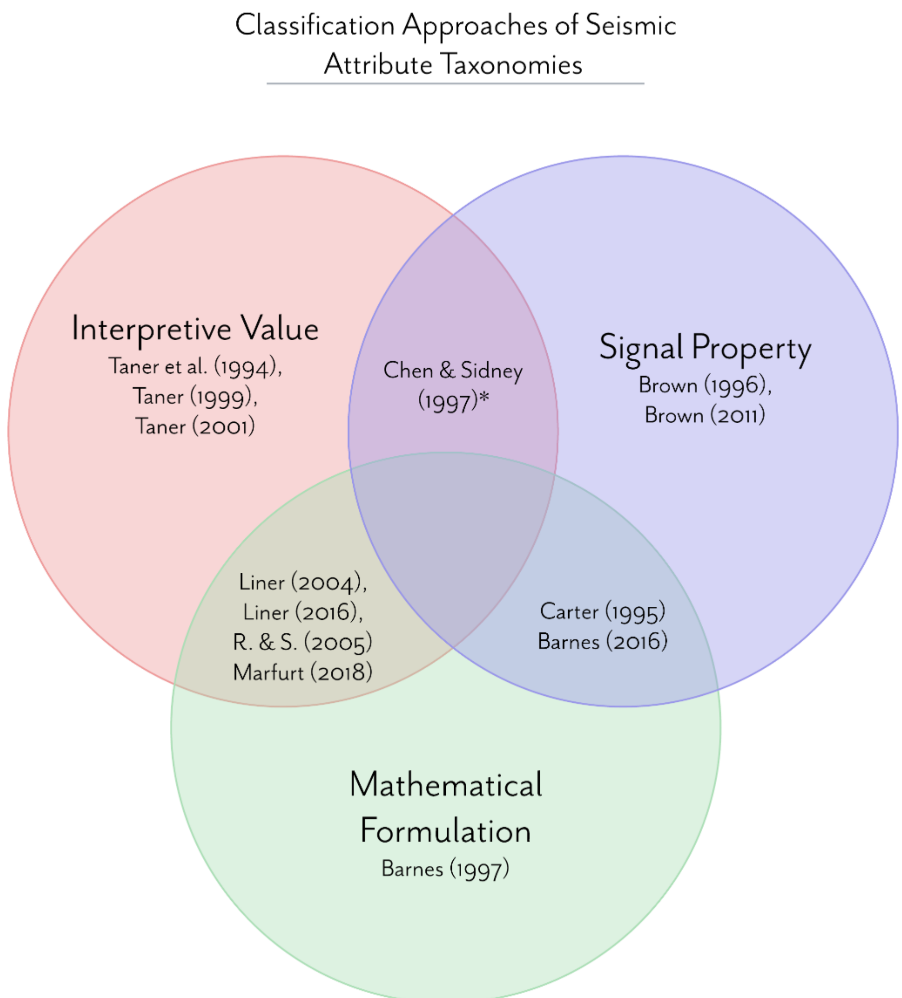


Figure 2.10: Classification Approaches of Seismic Attribute Taxonomies
A graphical representation of the categorization of the discussed seismic attribute taxonomies. The asterisk shows a taxonomy where the authors use multiple domains with discrete organizations for each. After identifying three data analysis domains used in seismic attribute analysis, we can classify all seismic attribute schemes based on the amount of contribution to each domain.

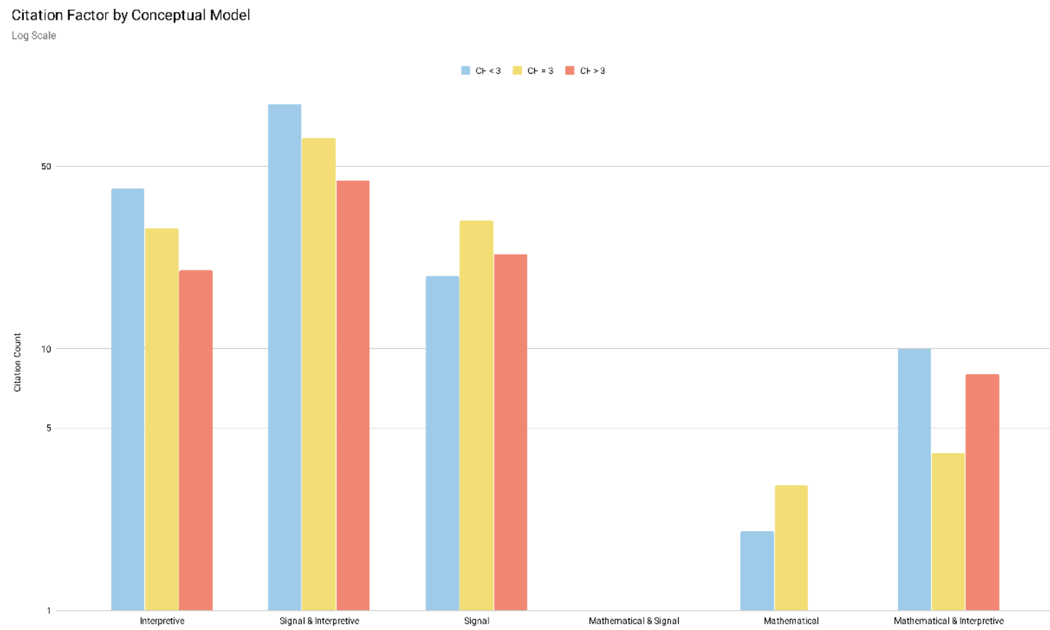


Figure 2.11: Citation Factor Count by Conceptual Model

Citation count groups by citation usage (citation factor) across the defined data analysis domains or conceptual model. The citation factor (CF) is useful as a proxy for the overall importance of one author's work to another based on the assumption that a longer discussion on a prior work is directly proportional to the perceived importance of that work by the citing author. We hypothesize that the optimal pattern that represents ideas in "mainstream" thought is achieved by a research cascade effect. This occurs as narrowly focused detailed work cites a particular article more often, its usage will cascade to the authors of broader, less focused work. The resulting pattern is that high CF scores are the smallest group, and low CF scores are the most common group. We have grouped citation factors into a lower half (CF<3), an upper half (CF>3), and a neutral (CF=3). We show this graph in log scale.

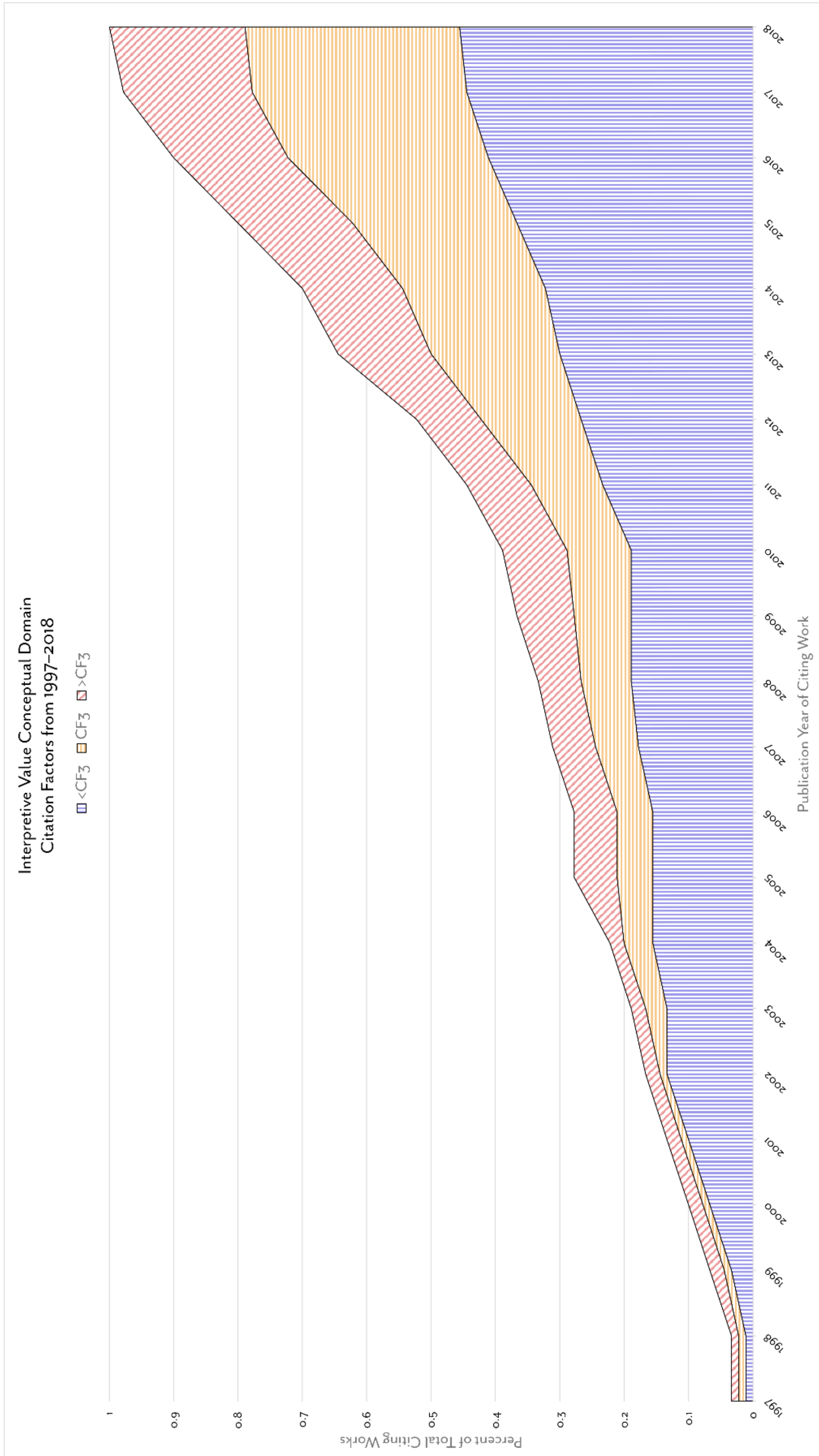


Figure 2.12: Interpretive Value Conceptual Domain Cumulative Chart
Citation factors grouped by low citation factor (CF<3), neutral (CF=3), and high citation factor (CF>3).

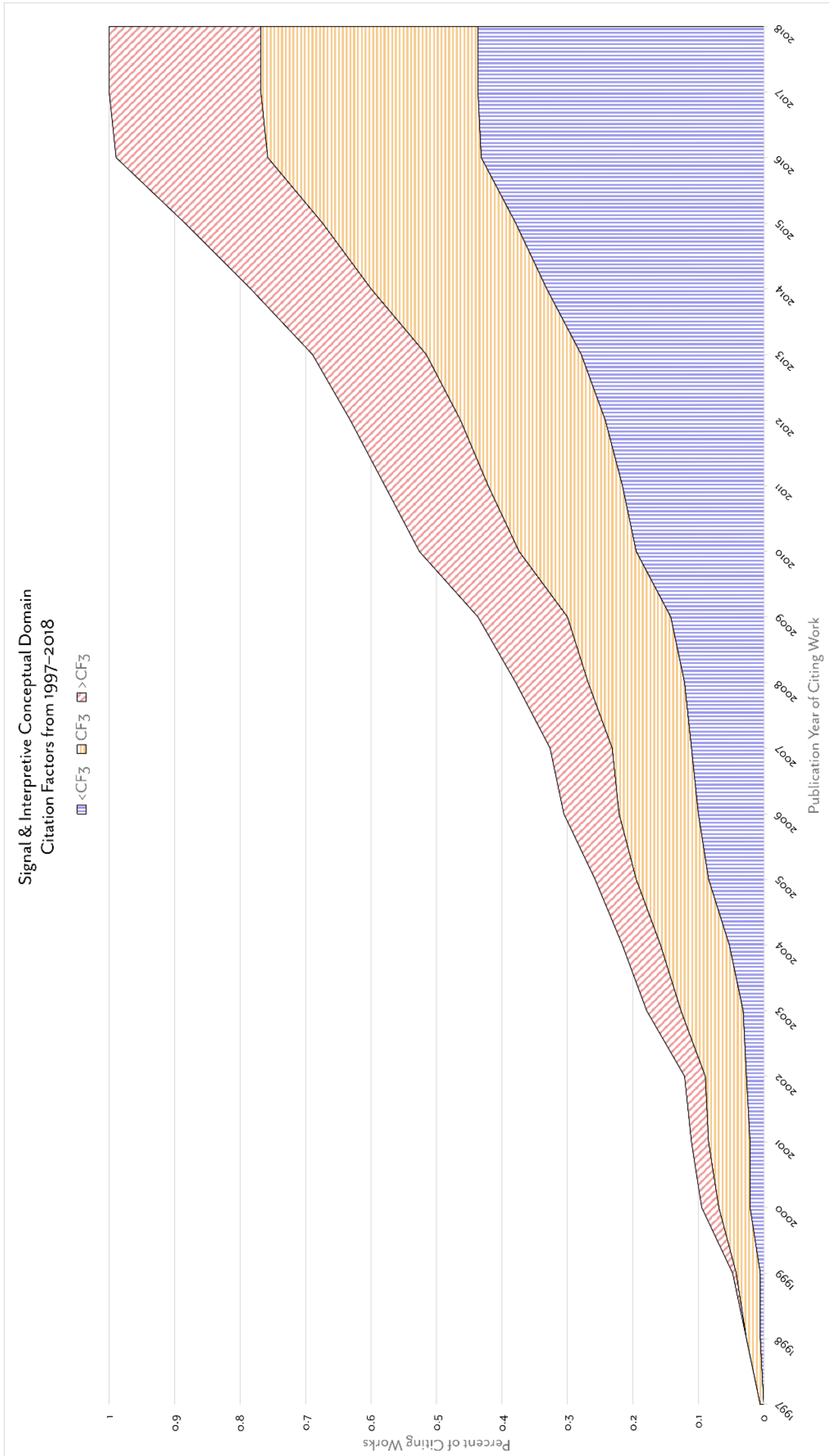


Figure 2.13: Signal & Interpretive Conceptual Domain Cum. Chart 1997–2018
Citation factors grouped by low citation factor (CF<3), neutral (CF=3), and high citation factor (CF>3).

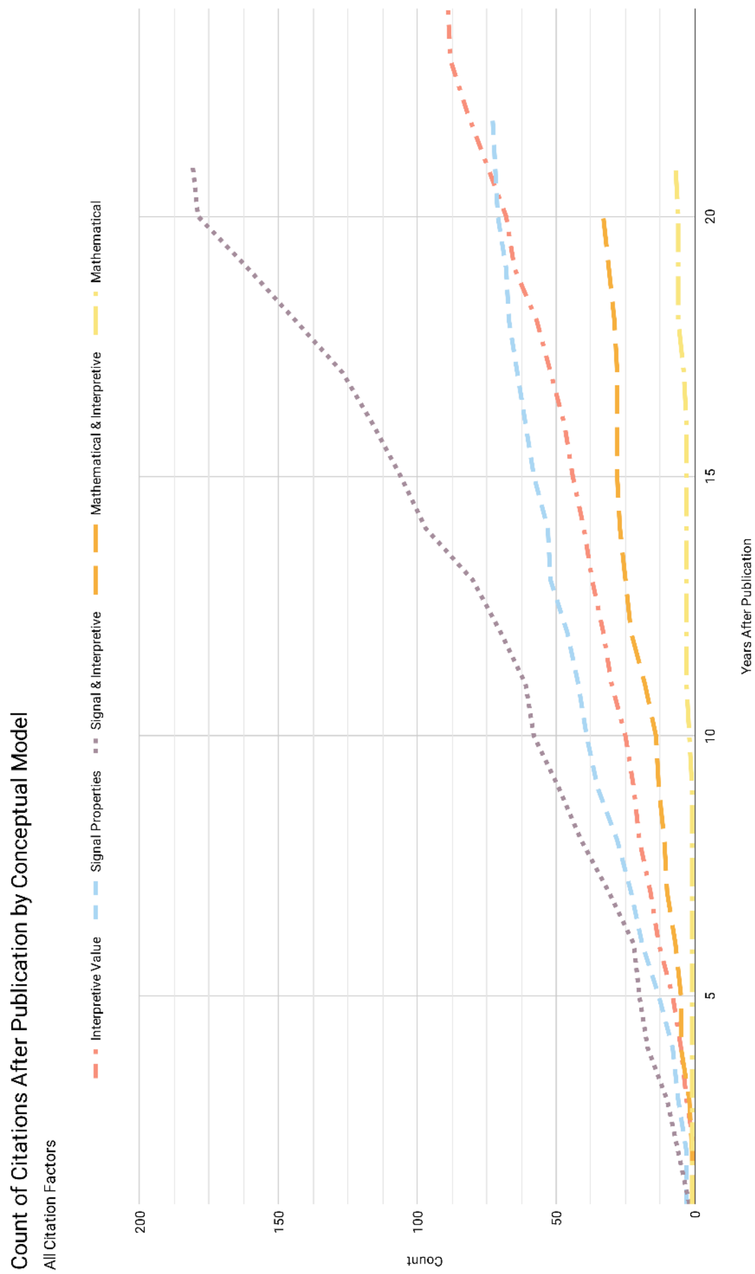


Figure 2.14: Count of Citation after Publication by Conceptual Model

Count of Citations after Publication by Conceptual Model. Total count of citing articles shown as years after initial publication. The “interpretive value” data analysis domain clearly offers significant advantage to other researchers as they communicate their ideas on seismic attribute usage. The crossover between the “signal property” and the “interpretive value” citations is interesting. We determine its cause by looking at Figure 2.2, where the low CF citations, which should be large, are small for the signal property data analysis domain (i.e., the signal property taxonomies never gained popularity with low citation factor publications).

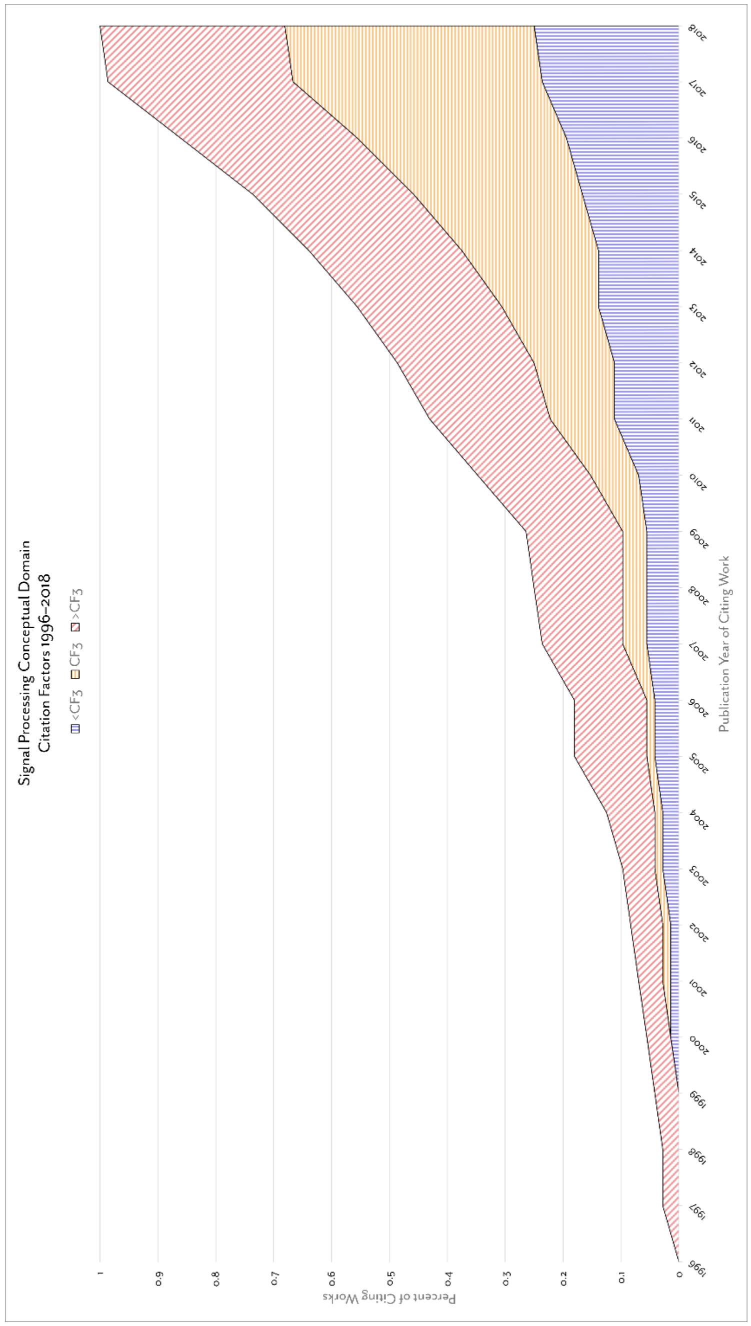


Figure 2.15: Signal Property Conceptual Domain Cumulative Chart 1997–2018
Citation factors grouped by low citation factor (CF<3), neutral (CF=3), and high citation factor (CF>3). The ratio of high CF to low CF values for the signal property conceptual domain is larger than any other attribute taxonomy group, which implies that among the citing articles, seismic attribute specialists value the signal property more than casual researchers. In absolute terms, Figure 2.10 further illustrates that even in absolute terms, specialists (high CF citations) prefer the signal taxonomy to the interpretive value taxonomies.

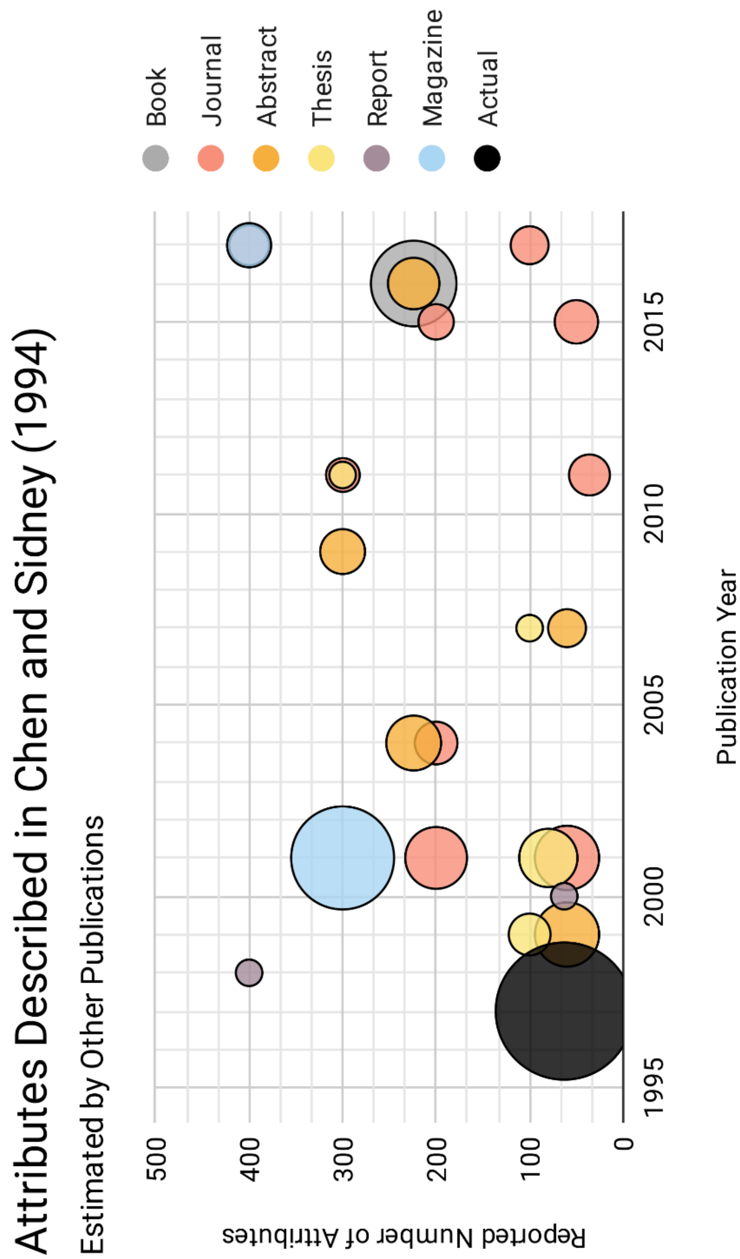


Figure 2.16: Attributes described in Chen and Sidney (1994)

Bubble chart illustrating the estimation or count of seismic attributes described or defined in Chen and Sidney (1994) as a function of time, colored by publication type. We assigned a value of 400 to extreme and imprecise estimates (e.g., “several hundred” or “hundreds”). The large black bubble represents the actual value. The size of the bubble chart indicates the number of citing articles for each publication.

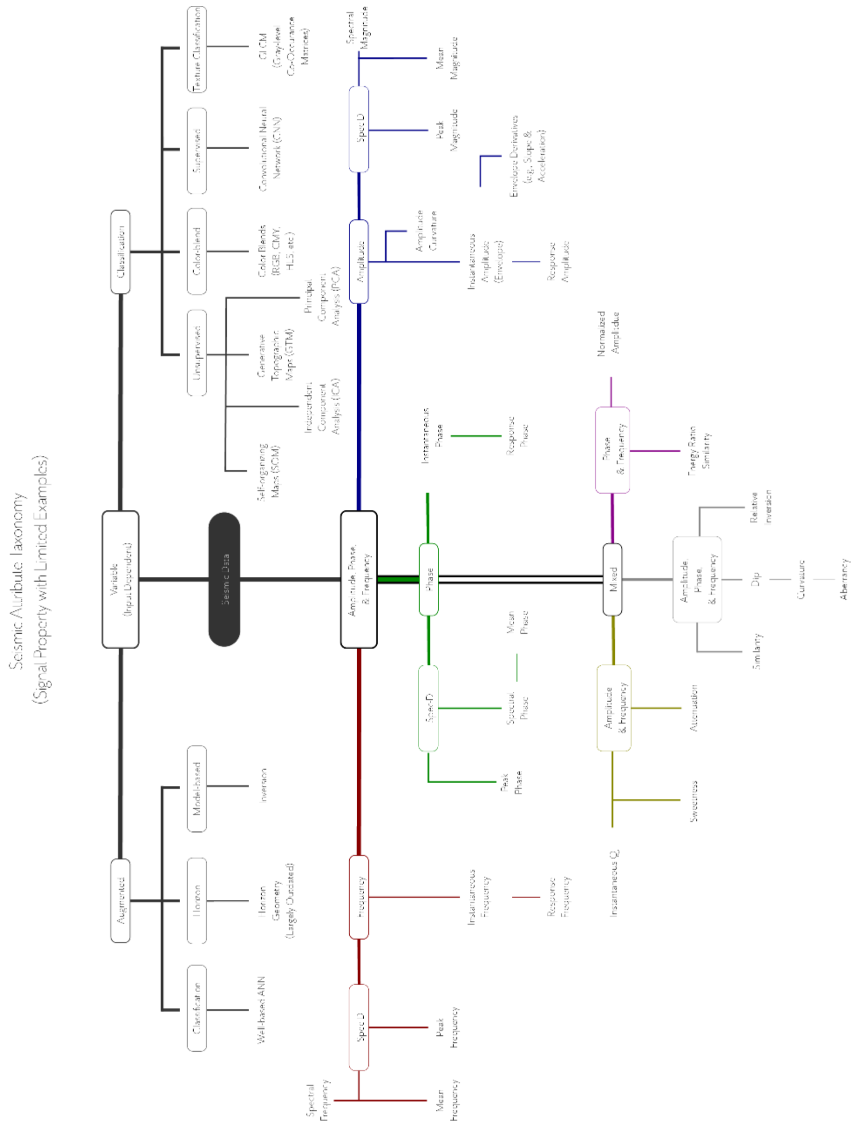


Figure 2.17: Attribute taxonomy using the signal property conceptual domain
Tree-style chart illustrating the portion of the signal that a given attribute interrogates. Beginning with the "seismic data" node, the attributes attached to the "variable" child node interrogate the portion of the signal their input also interrogates. We represent frequency attributes with red (#880000), amplitude attributes with blue (#000088), phase attributes with green (#008800). We represent the mixture of signal properties with the corresponding color mixture (i.e., yellow-green (#880088) for amplitude and frequency, magenta (#888800) for phase and frequency, and gray (#888888) for all portions of the signal). We placed these mixed attributes below the "phase" node for compactness.

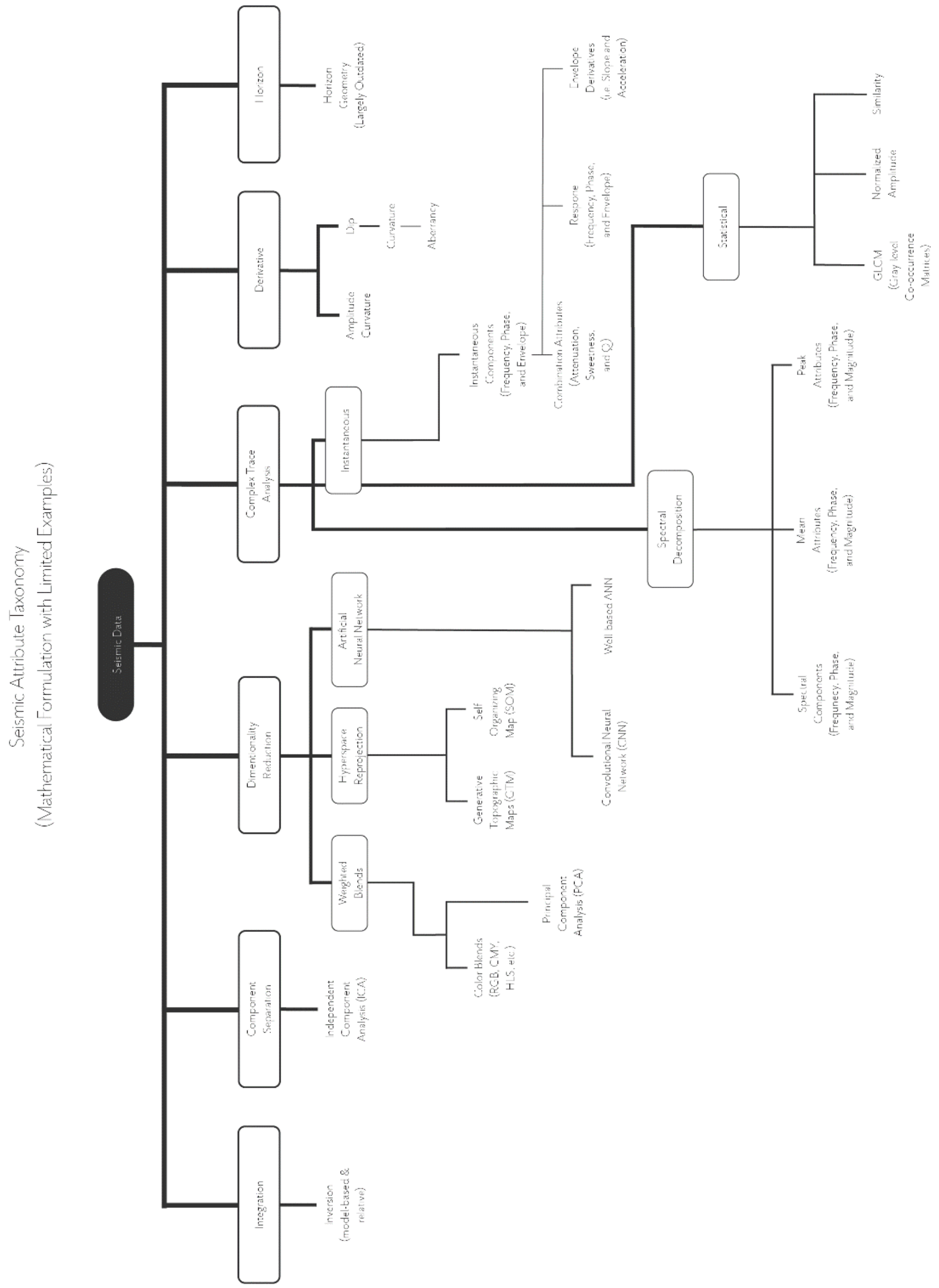


Figure 2.18: Attribute taxonomy using the mathematical conceptual domain
Tree-style chart illustrating the family of mathematical property that an attribute generally represents. We added "component separation" and "dimensionality reduction" to describe these often complex and nonlinear processes. Derivative attributes may be of particular interest to interpreters because of the high-pass filter effect that derivatives have on a signal, which may result in attributes with emphasized high-frequency noise. Beyond this first-order categorization, we used data linage to differentiate attributes further.

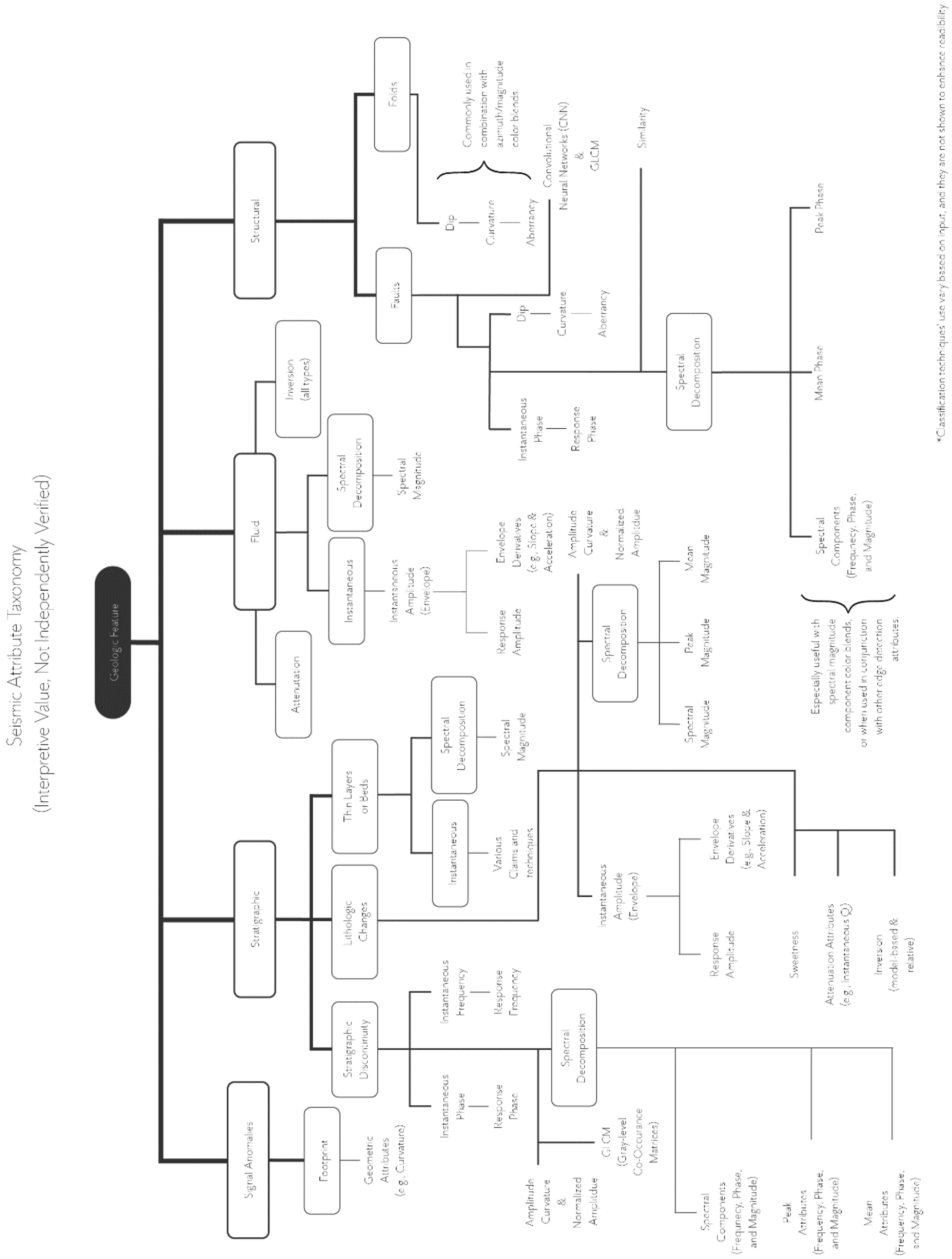


Figure 2.19: Attribute taxonomy using the interpretive value conceptual domain
Tree-style chart illustrating the use of a seismic attribute to identify a variety of geoscience objectives, as commonly interpreted by professional seismic interpreters. As mentioned previously, it is necessary to duplicate individual attributes because interpreters often find them to have multiple uses. We omitted classification attributes from this list due to the property inheritance that classification attributes derive from their constituents.

Tables and Charts

Table 2.1: Seismic attribute taxonomy correlation table

Graphical correlation of each example attribute used in this paper across data analysis or conceptual domains. The first seven columns (blue) after the attribute name describe the placement of the attribute on the signal property domain taxonomy, the next six columns (orange) describe the placement of the attribute on the mathematical formulation taxonomy, and the last four columns (green) describe the placement of the attribute on the interpretive value taxonomy. Where researchers claim the effectiveness of an attribute for multiple interpretive goals, we placed multiple entries on the interpretive value section of this chart.

	F	P	A	AF	PF	APF	V	I	CS	DR	CA	D	H	SA	S	F	St
mean frequency	x										x				x		
peak frequency	x										x				x		
spectral frequency	x										x				x		
instantaneous frequency	x										x				x		
response frequency	x										x				x		
peak phase		x									x				x		x
spectral phase		x									x				x		x
response phase		x									x				x		x
instantaneous phase		x									x				x		x
mean phase		x									x				x		x
instantaneous q				x							x				x		
sweetness				x							x				x		
attenuation				x							x				x	x	
energy ratio similarity					x						x			x			
normalized amplitude					x												
dip						x						x					x
curvature						x						x		x			x
aberrancy						x						x		x			x
instantaneous amplitude (envelope)			x								x				x	x	
response amplitude			x								x				x	x	
envelope derivatives			x								x				x	x	
peak magnitude mean magnitude			x								x				x	x	
spectral magnitude			x								x				x	x	
well-based ANN							x			x							
horizon geometry							x						x				x
model-based inversion							x	x							x	x	
self-organizing maps (SOM)							x			x							
independent component analysis (ICA)							x		x								
generative topographic maps (GTM)							x			x							
principal component analysis (PCA)							x			x							
color blends							x			x							
convolutional neural networks (CNN)							x			x				x	x		
relative inversion						x		x							x	x	
similarity						x					x			x			x
gray-level co-occurance matricies (GLCM)							x				x				x		x
amplitude curvature			x									x			x		

F=Frequency
A=Amplitude
P=Phase
V=Variable

CS=Component Separation
DR=Dimentionality Reduction
CA=Complex Trace Analysis
D=Derivative
H=Horizon
I=Integration

SA=Signal Anomalies
S=Stratigraphic
F=Fluid
St=Structural

Table 2.2: Seismic attribute definitions

Name	Description	References
aberrancy	In mathematics, aberrancy is the deviation from a well-behaved curve. In geophysics, aberrancy is the mathematical third derivative of the structure. It is often incorrectly called "flexure." While flexure is the bend or curve itself, aberrancy is the rate of change of the curve.	(Carnot, 1803; Smith, 1898; Schot, 1978; Qi and Marfurt, 2018)
amplitude curvature	While amplitude gradient is the rate of change of the amplitude values, amplitude curvature is the rate of change of the amplitude gradient. The use of "curvature" does not imply a geometric shape, rather it denotes a second derivative.	(Chopra and Marfurt, 2007)
amplitude (signal) envelope or instantaneous amplitude (A_i)	Defined as the square root of the sum of the real and imaginary traces squared: $A_i(t) = \sqrt{(f_i(t)^2 + f_i^*(t)^2)}$	(Taner et al., 1979)
attenuation (attribute)	Any method to obtain an estimation of the seismic trace's signal a'tenuation.	
color blend	Using a projected color space to represent multiple single attributes together. Often practitioners use the RGB, CMY, HSL, or HSV color spaces.	(Balch, 1971; Joblove and Greenberg, 1978; Onstott et al., 1984; Liu and Marfurt, 2007; Guo et al., 2008; Dao and Marfurt, 2011; Purves and Basford, 2011; Marfurt, 2015)
convolutional neural networks (CNN)	A class of artificial neural networks that use a mathematical convulsion in at least one of their computational layers. CNNs are commonly used to classify images based on training data.	(Lecun et al., 1998; LeCun et al., 2015; Schmidhuber, 2015; Krizhevsky et al., 2017)

Name	Description	References
dip	The first derivative of the geologic structure, or the rate of change in the structure.	(Marfurt, 2006)
energy ratio similarity	A structurally orientated measurement of similarity using an eigenstructure coherence algorithm, defined as the ratio of the Karhunen-Loeve filtered data over the total energy within an analysis window.	(Gersztenkorn and Marfurt, 1999)
envelope derivatives	Mathematical derivatives of the amplitude envelope.	(Barnes, 2016)
generative topographic maps (GTM)	A probabilistic reformulation of self-organizing maps (SOMs) that requires a probability density function over the data, employs a cost function to quantify the confidence of the final clustering results, and uses an EM optimization algorithm.	(Bishop et al., 1998; Roy et al., 2014)
gray-level co-occurance matricies (GLCM)	A series of attributes calculated by various statistical measures over a window following a rescaling of the samples. Also known more formally as a co-occurrence matrix, co-occurrence matrices are heavily used in both medical and satellite image analysis, where analysts use the co-occurrence matrix to measure the texture of the dominantly gray-scale images.	(Haralick et al., 1973; Yenugu et al., 2010; Gao, 2011; Nanni et al., 2013)
horizon geometry	Any geometric calculation using an interpreted horizon as the input. These calculations are generally more simple and less compute intensive than their volumetric counterparts. Such horizon-based attributes are no longer recommended.	(Roberts, 2001)
independent component analysis (ICA)	A computational method to separate a multivariate signal into its additive subcomponents. ICA assumes the subcomponents are non-Gaussian and are statistically independent from one another. A nonlinear or linear approach may be used.	(Comon, 1994; Desodt, 1994; Lubo-Robles and Marfurt, 2018)

Name	Description	References
instantaneous frequency (f_i)	Defined as the derivative of instantaneous phase with respect to time.	(Taner et al., 1979)
instantaneous phase (φ_i)	Defined as the angle whose tangent is the ratio of the imaginary trace to the real trace.	(Taner et al., 1979)
instantaneous quality factor (q_i)	Defined as the ratio of instantaneous frequency to two times the instantaneous decay rate, σ_i: $$q_i = \frac{-\pi f_i}{\sigma_i}$$	(Barnes, 1993)
mean frequency	Spectral magnitude-weighted arithmatic average (mean) frequency, often an output of various spectral decomposition algorithms.	(Partyka et al., 1999; Chopra and Marfurt, 2007)
mean magnitude	Range-trimmed arithmatic average (mean) magnitude, often an output of various spectral decomposition algorithms.	(Partyka et al., 1999; Chopra and Marfurt, 2007)
model-based inversion	A method to obtain the rock and fluid properties from the collected seismic data. A non-unique model of the elastic properties covering frequencies that are not represented in the seismic data, typically the lower frequency band, allows for absolute (as opposed to relative) estimations of rock and fluid properties.	(Cooke and Schneider, 1983; Oldenburg et al., 1983; Walker and Ulrych, 1983; Russell and Hampson, 1991; Aki and Richards, 2009; Menke, 2018)
peak frequency	The frequency value at the peak of the spectral magnitude, often associated with spectral decomposition.	(Partyka et al., 1999; Chopra and Marfurt, 2007)

Name	Description	References
peak magnitude	The value at the peak (highest value) of the spectral magnitude, often associated with spectral decomposition.	(Partyka et al., 1999; Chopra and Marfurt, 2007)
peak phase	The phase value at the peak of the spectral magnitude, often associated with spectral decomposition.	(Partyka et al., 1999; Chopra and Marfurt, 2007)
principal component analysis (PCA), Karhunen-Loève transform, singular value decomposition, or eigenvalue decomposition	A method of reprojection of the input data into an orthonormal basis, where any individual dimension is linearly uncorrelated to any other individual dimension. The principal components of the input data are the eigenvectors of the covariance matrix. PCA is a method of dimensionality reduction where the higher dimensions of the input data represent data with lower overall variance. Such higher dimensional data is commonly assumed to be redundant data or noise.	(Pearson, 1901; Golub, 1996; Bengio et al., 2013; Forkman et al., 2019)
relative inversion	A method to estimate the rock and fluid properties from seismic data. Because seismic data do not cover a continuous band of signal (there is a gap below a data-dependent low frequency), these methods allow for relative (as opposed to absolute) estimations of rock and fluid properties.	(Gassaway and Richgels, 1983; Shuey, 1985; Latimer et al., 2000)
Name	**Description**	**References**
response amplitude	The value of the instantaneous amplitude at envelope peaks carried as a constant to the next envelope peak.	(Bodine, 1984)
response frequency	The value of the instantaneous frequency at envelope peaks carried as a constant to the next envelope peak.	(Bodine, 1984)

Name	Description	References
response phase	The value of the instantaneous phase at envelope peaks carried as a constant to the next envelope peak.	(Bodine, 1984)
self-organizing maps (SOM)	An unsupervised classification method to map multi-dimensional input data onto a lower dimensional, typically 2D, latent space. SOMs operate through competitive learning and use a neighborhood function to preserve the topological properties of the input space.	(Kohonen, 1982, 2001; Kohonen and Honkela, 2007)
similarity	One of a number of seismic attributes that, generally, uses a group of samples in the seismic data, computes a value based on how similar the central reference sample is to the remaining samples, and returns a value, typically between zero and one.	(Bahorich and Farmer, 1995; Gersztenkorn and Marfurt, 1996; Luo et al., 1996, 2003; Marfurt et al., 1998)
spectral voice (band-limited reconstruction)	Any of a set of outputs from one of the many spectral decomposition algorithms where the phase and magnitude, as a function of frequency, are used to reconstruct a band-limited version of the seismic.	(Chopra and Marfurt, 2007)
spectral magnitude	Any of a set of outputs from one of the many spectral decomposition algorithms that returns a set of data that represents the signal magnitude typically organized as a function of frequency.	(Chopra and Marfurt, 2007)
spectral phase	Any of a set of outputs from one of the many spectral decomposition algorithms that returns a set of data that represents the signal phase typically organized as a function of frequency.	(Chopra and Marfurt, 2007)

Name	Description	References
sweetness (S_i)	Defined as the ratio of instantaneous amplitude to the square root of instantaneous frequency: $$S_i = \frac{A_i}{\sqrt{f_i}}$$	(Radovich and Oliveros, 1998; Hart, 2008)
well-based ANN	Often employed as a feed-forward neural network, well-based ANN refers to the general practice of applying known information taken from a well log and extrapolating it to a more sparsely sampled seismic data volume. Typically accomplished by applying weighted instantaneous seismic attributes combined with nonlinear operators to match a desired well log. These combined volumes may represent a pseudo well log property; however, the ability for the pseudo property to accurately predict the unknown data is data-dependent, and it is typically assumed that the well logs used capture the entire possible variability of the geologic section in question.	(Todorov et al., 1997, 1998; Hampson et al., 2001)

References

Adams, D., and D. Markus, 2013, Systematic error in instantaneous attributes: SEG Technical Program Expanded Abstracts, 1363–1367.

Aki, K., and P. G. Richards, 2009, Quantitative Seismology, Second Edition.: University Science Books.

Al-Dossary, S., and K. J. Marfurt, 2006, 3D volumetric multispectral estimates of reflector curvature and rotation: Geophysics, **71**, P41–P51.

Bahorich, M. S., and S. L. Farmer, 1995, 3-D seismic discontinuity for faults and stratigraphic features: The coherence cube: SEG Technical Program Expanded Abstracts, 93–96.

Balch, A. H., 1971, Color Sonagrams: A New Dimension in Seismic Data Interpretation: Geophysics, **36**, 1074–1098.

Barnes, A., 2006, Too many seismic attributes: CSEG Recorder, **31**, 40–45.

Barnes, A., 2016, Handbook of Poststack Seismic Attributes: Society of Exploration Geophysicists.

Barnes, A., 2017, Instantaneous attributes and subseismic resolution: SEG Technical Program Expanded Abstracts, 2018–2022.

Barnes, A. E., 1993, Instantaneous spectral bandwidth and dominant frequency with applications to seismic reflection data: Geophysics, **58**, 419–428.

Barnes, A. E., 1997, Genetic classification of complex seismic trace attributes: .

Bengio, Y., A. Courville, and P. Vincent, 2013, Representation learning: a review and new perspectives: IEEE Transactions on Pattern Analysis and Machine Intelligence, **35**, 1798–1828.

Bishop, C. M., M. Svensén, and C. K. I. Williams, 1998, Developments of the generative topographic mapping: Neurocomputing, **21**, 203–224.

Bodine, J. H., 1984, Waveform analysis with seismic attributes: SEG Technical Program Expanded Abstracts, **69**, 505–509.

Brown, A., 1996, Seismic attributes and their classification: The Leading Edge, **15**, 1090–1090.

Brown, A. R., 2011, Interpretation of Three-Dimensional Seismic Data: American Association of Petroleum Geologists.

Carnot, L. N. M., 1803, Géométrie de Position: J. B. M. Duprat.

Carter, D. C., 1995, Use of Windowed Seismic Attributes in 3D Seismic Facies Analysis and Pattern Recognition: International Symposium on Sequence Stratigraphy, 73–87.

Castagna, J. P., and M. M. Backus, 1993, Offset Dependent Reflectivity-Theory and Practice of AVO (Investigations in Geophysics No. 8) (Investigations in Geophysics, Vol 8), Pristine Condition Like New Edition.: Society Of Exploration Geophysicists.

Chen, Q., and S. Sidney, 1997a, Advances in seismic attribute technology: SEG Technical Program Expanded Abstracts.

Chen, Q., and S. Sidney, 1997b, Seismic attribute technology for reservoir forecasting and monitoring: The Leading Edge, **16**, 445–448.

Chopra, S., and K. J. Marfurt, 2007, Seismic Attributes for Prospect Identification and Reservoir Characterization: Society of Exploration Geophysicists.

Chopra, S., and J. P. Castagna, 2014, AVO: SEG Investigations in Geophysics 16: Society of Exploration Geophysicists.

Chopra, S., and K. J. Marfurt, 2019, Multispectral, multiazimuth, and multioffset coherence attribute applications: Interpretation, **7**, SC21–SC32.

Comon, P., 1994, Independent component analysis, A new concept? Signal Processing, **36**, 287–314.

Cooke, D. A., and W. A. Schneider, 1983, Generalized linear inversion of reflection seismic data: Geophysics, **48**, 665–676.

Costa, F. A., C. R. Suarez, D. J. Sarzenski, and C. C. Ferreira Guedes, 2007, Using Seismic Attributes in Petrophysical Reservoir Characterization: Latin American & Caribbean Petroleum Engineering Conference.

Dao, T., and K. J. Marfurt, 2011, The value of visualization with more than 256 colors: SEG Technical Program Expanded Abstracts, 941–945.

Desodt, G., 1994, Complex independent components analysis applied to the separation of radar signals: Proceedings of EUSIPCO-90, 665–668.

Forkman, J., J. Josse, and H.-P. Piepho, 2019, Hypothesis Tests for Principal Component Analysis When Variables are Standardized: Journal of Agricultural, Biological, and Environmental Statistics, **24**, 289–308.

Gao, D., 2011, Latest developments in seismic texture analysis for subsurface structure, facies, and reservoir characterization: A review: Geophysics, **76**, W1–W13.

Gassaway, G. S., and H. J. Richgels, 1983, SAMPLE: seismic amplitude measurement for primary lithology estimation: SEG Technical Program Expanded Abstracts 1983, **39**, 610–613.

Gersztenkorn, A., and K. J. Marfurt, 1996, Eigenstructure based coherence computations: SEG Technical Program Expanded Abstracts, 328–331.

Gersztenkorn, A., and K. J. Marfurt, 1999, Eigenstructure-based coherence computations as an aid to 3-D structural and stratigraphic mapping: Geophysics, **64**, 1468–1479.

Golub, G. H., 1996, Matrix Computations, 3rd ed..: Johns Hopkins University Press.

Guo, H., S. Lewis, and K. J. Marfurt, 2008, Mapping multiple attributes to three- and four-component color models — A tutorial: Geophysics, **73**, W7–W19.

Hampson, D., T. Todorov, and B. Russell, 2000, Using multi-attribute transforms to predict log properties from seismic data: Exploration Geophysics, **31**, 481–487.

Hampson, D., J. Schuelke, and J. Quirein, 2001, Use of multiattribute transforms to predict log properties from seismic data: Geophysics, **66**, 220–236.

Haralick, R. M., K. Shanmugam, and I. Dinstein, 1973, Textural Features for Image Classification: IEEE Transactions on Systems, Man, and Cybernetics, **SMC-3**, 610–621.

Hart, B. S., 2008, Channel detection in 3-D seismic data sing sweetness: AAPG Bulletin, **92**, 733–742.

Hilterman, F. J., 2001, Seismic Amplitude Interpretation, Distinguished Instructor Short Course: Society of Exploration Geophysicists.

Hinton, G. E., S. Osindero, and Y.-W. Teh, 2006, A fast learning algorithm for deep belief nets: Neural Computation, **18**, 1527–1554.

Hsu, F.-H., 2004, Behind Deep Blue: Building the Computer That Defeated the World Chess Champion: Princeton University Press.

Joblove, G. H., and D. Greenberg, 1978, Color spaces for computer graphics: Proceedings of the 5th Annual Conference on Computer Graphics and Interactive Techniques, 20–25.

Jouppi, N. P., C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers, R. Boyle, P.-L. Cantin, C. Chao, C. Clark, J. Coriell, M. Daley, M. Dau, J. Dean, B. Gelb, T. V. Ghaemmaghami, R. Gottipati, W. Gulland, R. Hagmann, C. R. Ho, D. Hogberg, J. Hu, R. Hundt, D. Hurt, J. Ibarz, A. Jaffey, A. Jaworski, A. Kaplan, H. Khaitan, D. Killebrew, A. Koch, N. Kumar, S. Lacy, J. Laudon, J. Law, D. Le, C. Leary, Z. Liu, K. Lucke, A. Lundin, G. MacKean, A. Maggiore, M. Mahony, K. Miller, R. Nagarajan, R. Narayanaswami, R. Ni, K. Nix, T. Norrie, M. Omernick, N. Penukonda, A. Phelps, J. Ross, M. Ross, A. Salek, E. Samadiani, C. Severn, G. Sizikov, M. Snelham, J. Souter, D. Steinberg, A. Swing, M. Tan, G. Thorson, B. Tian, H. Toma, E. Tuttle, V. Vasudevan, R. Walter, W. Wang, E. Wilcox, and D. H. Yoon, 2017, In-Datacenter Performance Analysis of a Tensor Processing Unit: Proceedings of the 44th Annual International Symposium on Computer Architecture, 1–12.

Kalkomey, C., 1997, Potential risks when using seismic attributes as predictors of reservoir properties: Leading Edge, **16**, 247–251.

Kim, Y., R. Hardisty, and K. J. Marfurt, 2019, Attribute selection in seismic facies classification: Application to a Gulf of Mexico 3D seismic survey and the Barnett Shale: Interpretation, **7**, SE281–SE297.

Klokov, A., and S. Fomel, 2012, Separation and imaging of seismic diffractions using migrated dip-angle gathers: Geophysics, **77**, S131–S143.

Kohonen, T., 1982, Self-organized formation of topologically correct feature maps: Biological Cybernetics, **43**, 59–69.

Kohonen, T., 2001, Self-Organizing Maps: Springer, Berlin, Heidelberg.

Kohonen, T., and T. Honkela, 2007, Kohonen network: Scholarpedia Journal, **2**, 1568.

Krizhevsky, A., I. Sutskever, and G. E. Hinton, 2017, ImageNet classification with deep convolutional neural networks: Communications of the ACM, **60**, 84–90.

Latimer, R. B., R. Davidson, and P. van Riel, 2000, An interpreter's guide to understanding and working with seismic-derived acoustic impedance data: Leading Edge, **19**, 242–256.

LeCun, Y., Y. Bengio, and G. Hinton, 2015, Deep learning: Nature, **521**, 436–444.

Lecun, Y., L. Bottou, Y. Bengio, and P. Haffner, 1998, Gradient-based learning applied to document recognition: Proceedings of the IEEE, **86**, 2278–2324.

Liner, C., 2016, Elements of 3D Seismology: Society of Exploration Geophysicists.

Liner, C., C. Li, A. Gersztenkorn, and J. Smythe, 2004, SPICE: A new general seismic attribute: SEG Technical Program Expanded Abstracts, 433–436.

Liu, J., and K. Marfurt, 2007, Multicolor display of spectral attributes: Leading Edge, **26**, 268–271.

Lubo-Robles, D., and K. J. Marfurt, 2018, Unsupervised seismic facies classification using independent component analysis: SEG Technical Program Expanded Abstracts, **2**, 1603–1607.

Luo, Y., W. G. Higgs, and W. S. Kowalik, 1996, Edge detection and stratigraphic analysis using 3D seismic data: SEG Technical Program Expanded Abstracts, 324–327.

Luo, Y., S. Al-Dossary, M. Marhoon, and M. Alfaraj, 2003, Generalized Hilbert transform and its applications in geophysics: Leading Edge, **22**, 198–202.

M. Turhan Taner, Naum M. Derzhi, Joel D. Walls, 2002, Method for generating an estimate of lithological characteristics of a region of the earth's subsurface: US Patent.

Marfurt, K., 2006, Robust estimates of 3D reflector dip and azimuth: Geophysics, **71**, P29–P40.

Marfurt, K., 2015, Techniques and best practices in multiattribute display: Interpretation, **3**, B1–B23.

Marfurt, K. J., 2018, Seismic Attributes as the Framework for Data Integration Throughout the Oilfield Life Cycle: Society of Exploration Geophysicists.

Marfurt, K. J., R. L. Kirlin, S. L. Farmer, and M. S. Bahorich, 1998, 3-D seismic attributes using a semblance-based coherency algorithm: Geophysics, **63**, 1150–1165.

Markidis, S., S. W. D. Chien, E. Laure, I. B. Peng, and J. S. Vetter, 2018, NVIDIA Tensor Core Programmability, Performance Precision: 2018 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), 522–531.

Meldahl, P., R. Heggland, B. Bril, and P. de Groot, 2001, Identifying faults and gas chimneys using multiattributes and neural networks: Leading Edge, **20**, 474–482.

Menke, W., 2018, Geophysical Data Analysis: Discrete Inverse Theory: Academic Press.

Nanni, L., S. Brahnam, S. Ghidoni, E. Menegatti, and T. Barrier, 2013, Different approaches for extracting information from the co-occurrence matrix: PloS One, **8**, e83554.

Odegard, J. E., P. Steeghs, R. G. Baraniuk, and C. S. Burrus, 1998, Rice Consortium for Computational Seismic Interpretation: Rice University.

Oldenburg, D. W., T. Scheuer, and S. Levy, 1983, Recovery of the acoustic impedance from reflection seismograms: Geophysics, **48**, 1318–1337.

Onstott, G. E., M. M. Backus, C. R. Wilson, and J. D. Phillips, 1984, Color display of offset dependent reflectivity in seismic data: SEG Technical Program Expanded Abstracts, 674–675.

Partyka, G., J. Gridley, and J. Lopez, 1999, Interpretational applications of spectral decomposition in reservoir characterization: The Leading Edge, **18**, 353–360.

Pearson, K., 1901, On lines and planes of closest fit to systems of points in space: The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, **2**, 559–572.

Pigott, J. D., M.-H. Kang, and H.-C. Han, 2013, First order seismic attributes for clastic seismic facies interpretation: Examples from the East China Sea: Journal of Asian Earth Sciences, **66**, 34–54.

Purves, S., and H. Basford, 2011, Visualizing geological structure with subtractive color blending: GCSSEPM Extended Abstracts.

Qi, X., and K. Marfurt, 2018, Volumetric aberrancy to map subtle faults and flexures: Interpretation, **6**, T349–T365.

Radovich, B. J., and R. B. Oliveros, 1998, 3-D sequence interpretation of seismic instantaneous attributes from the Gorgon Field: Leading Edge, **17**, 1286–1293.

Randen, T., and L. Sønneland, 2005, Atlas of 3D Seismic Attributes, *in* A. Iske and T. Randen, eds., Mathematical Methods and Modelling in Hydrocarbon Exploration and Production, Springer, 23–46.

Rijks, E. J. H., and J. C. E. M. Jauffred, 1991, Attribute extraction: An important application in any detailed 3-D interpretation study: Leading Edge, **10**, 11–19.

Roberts, A., 2001, Curvature attributes and their application to 3D interpreted horizons: First Break, **19.2**, 85–100.

Roden, R., and C. W. Chen, 2017, Interpretation of DHI characteristics with machine learning: First Break, **35**, 55–63.

de Rooij, M., and K. Tingdahl, 2003, Fault detection with meta-attributes: SEG Technical Program Expanded Abstracts 2003, 354–357.

Roy, A., A. S. Romero-Peláez, T. J. Kwiatkowski, and K. J. Marfurt, 2014, Generative topographic mapping for seismic facies estimation of a carbonate wash, Veracruz Basin, southern Mexico: Interpretation, **2**, SA31–SA47.

Rummerfield, B. F., 1954, Reflection Quality, A Fourth Dimension: Geophysics, **19**, 684–694.

Russell, B., and D. Hampson, 1991, Comparison of poststack seismic inversion methods, *in* SEG Technical Program Expanded Abstracts, Society of Exploration Geophysicists, 876–878.

Saggaf, M. M., M. N. Toksoz, and H. M. Mustafa, 2000, Application of Smooth Neural Networks for Inter-Well Estimation of Porosity from Seismic Data: Massachusetts Institute of Technology. Earth Resources Laboratory.

Samuel, A. L., 1959, Some studies in machine learning using the game of Checkers: IBM Journal of Research and Development.

Schmidhuber, J., 2015, Deep learning in neural networks: an overview: Neural Networks: The Official Journal of the International Neural Network Society, **61**, 85–117.

Schot, S. H., 1978, Aberrancy: Geometry of the Third Derivative: Mathematics Magazine, **51**, 259–275.

Shuey, R. T., 1985, A simplification of the Zoeppritz equations: Geophysics, **50**, 609–614.

Simonyan, K., and A. Zisserman, 2014, Very Deep Convolutional Networks for Large-Scale Image Recognition: ArXiv [Cs.CV].

Smith, W. B., 1898, Infinitesimal Analysis, by William Benjamin Smith: The Macmillan Company.

Smythe, J., A. Gersztenkorn, B. Radovich, C.-F. Li, and C. Liner, 2004, Gulf of Mexico shelf framework interpretation using a bed-form attribute from spectral imaging: Leading Edge, **23**, 921–926.

Taner, M. T., 1997, Kohonen's Self Organizing Networks with "Conscience": Rock Solid Images.

Taner, M. T., 1999, Seismic Attributes, Their Classification And Projected Utilization: 6th International Congress of the Brazilian Geophysical Society.

Taner, M. T., 2001, Seismic attributes: CSEG Recorder, **26**, 48–56.

Taner, M. T., and R. E. Sheriff, 1977, Application of Amplitude, Frequency, and Other Attributes to Stratigraphic and Hydrocarbon Determination, *in* C. E. Payton, ed., Seismic Stratigraphy: Applications to Hydrocarbon Exploration (AAPG Memoir 26), , . AAPG Special VolumesAmerican Association of Petroleum Geologists, 301–327.

Taner, M. T., F. Koehler, and R. E. Sheriff, 1979, Complex seismic trace analysis: Geophysics, **44**, 1041–1063.

Taner, M. T., J. Walls, and G. Taylor, 2001, Seismic Attributes, Their Use in Petrophysical Classification: 63rd EAGE Conference & Exhibition.

Taner, M. T., J. S. Schuelke, R. O'Doherty, and E. Baysal, 1994, Seismic attributes revisited: SEG Technical Program Expanded Abstracts, **36**, 1104–1106.

Tayyab, M. N., S. Asim, M. M. Siddiqui, M. Naeem, S. H. Solange, and F. K. Babar, 2017, Seismic attributes' application to evaluate the Goru clastics of Indus Basin, Pakistan: Arabian Journal of Geosciences, **10**, 158.

Todorov, T., D. Hampson, and B. Russell, 1997, Sonic Log Predictions Using Seismic Attributes: University of Calgary.

Todorov, T. I., R. R. Stewart, and D. P. Hampson, 1998, Porosity Prediction Using Attributes from 3C–3D Seismic Data: researchgate.net.

Tukey, J. W., 1962, The Future of Data Analysis: Annals of Mathematical Statistics, **33**, 1–67.

Turhan Taner, M., 2002, System for estimating the locations of shaley subsurface formations: US Patent.

Walker, C., and T. J. Ulrych, 1983, Autoregressive recovery of the acoustic impedance: Geophysics, **48**, 1338–1350.

Walls, J. D., M. T. Taner, T. Guidish, G. Taylor, D. Dumas, and N. Derzhi, 1999, North Sea reservoir characterization using rock physics, seismic attributes, and neural networks; a case history: SEG Technical Program Expanded Abstracts, **57**, 1572–1575.

Walls, J. D., M. T. Taner, G. Taylor, M. Smith, M. Carr, N. Derzhi, J. Drummond, D. McGuire, S. Morris, J. Bregar, and J. Lakings, 2000, Seismic reservoir characterization of a mid-continent fluvial system using rock physics, poststack seismic attributes and neural networks; a case history: SEG Technical Program Expanded Abstracts, **57**, 1437–1439.

Walls, J. D., M. T. Taner, G. Taylor, M. Smith, M. Carr, N. Derzhi, J. Drummond, D. McGuire, S. Morris, J. Bregar, and J. Lakings, 2002, Seismic reservoir characterization of a U.S. Midcontinent fluvial system using rock physics, poststack seismic attributes, and neural networks: Leading Edge, **21**, 428–436.

Xing, L., V. Aarre, A. Barnes, T. Theoharis, N. Salman, and E. Tjåland, 2017, Instantaneous Frequency Seismic Attribute Benchmarking: SEG Technical Program Expanded Abstracts.

Xing, L., V. Aarre, A. E. Barnes, T. Theoharis, N. Salman, and E. Tjåland, 2019, Seismic attribute benchmarking on instantaneous frequency: Geophysics, **84**, O63–O72.

Yenugu, M. (moe), K. J. Marfurt, and S. Matson, 2010, Seismic texture analysis for reservoir prediction and characterization: Leading Edge, **29**, 1116–1121.

Zhang, R., and J. Castagna, 2011, Seismic sparse-layer reflectivity inversion using basis pursuit decomposition: Geophysics, **76**, R147–R158.

1977, Seismic Stratigraphy: Applications to Hydrocarbon Exploration (C. E. Payton, ed.,): American Association of Petroleum Geologists.

2014, Understanding Seismic Anisotropy in Exploration and Exploitation, Second Edition, Second Edition. (L. Thomsen, ed.,): The Society of Exploration Geophysicists.

2007, Artificial General Intelligence (B. Goertzel and C. Pennachin, eds.,): Springer, Berlin, Heidelberg.

2012, Characterizing the Robustness of Science: After the Practice Turn in Philosophy of Science (L. Soler, E. Trizio, T. Nickles, and W. Wimsatt, eds.,): Springer, Dordrecht.

Appendix A: Data Used in Analysis

We gained the data regarding the number of citations for particular classification schemes by using computer programs and human interaction to scrape data from the following databases: Crossref (https://search.crossref.org), Google Scholar (https://scholar.google.com), Microsoft Academic Search (https://academic.microsoft.com), Scopus (https://www.scopus.com/ /home.uri), Web of Science (http://webofscience.com), University of Oklahoma Libraries (https://libraries.ou.edu), and ResearchGate (https://www.researchgate.net). The data represented a cross-section of relevant publications in geoscience. We categorize the data as peer review journals, published books, conference papers, non-peer reviewed technical magazines, technical reports (both government and consortia), and theses and dissertations.

The resulting data is what we term "raw data." By using computer-based data integration (colloquially referred to as "database scraping"), we accumulated over 2,100 citing works. Following a manual review of each work, we created a list of citing works that explicitly use one of the seismic attribute classification schemes. These schemes are outlined in the section "Historical Usage." The resulting list of citing works is what we term "pertinent data." Table A-1 is a subset of the pertinent data. This is the 287 citing works that we used in our review. Because of the increasingly global nature of the scientific discussion, we could find many citing works that we did not have the time or resources to translate fully. Table A-2 is a list of 80 such works. We will place the data on the website, https://www.seismicinterpretation.org for use by the community:

- Raw data — over 2,100 individual citing works
- Pertinent data — over 377 individual citing works after a manual review of the "raw data."
- Data used for citation analysis — 287 individual citing works that we used in this review.

Data not used for citation analysis — 80 individual citing works that remain untranslated, and we did not use them in this review.

Table A-1: Publications used for citation analysis

Authors	Title	Publication	DOI
Zhao-Ping M,Yan-Sheng GUO,Yun W,Jie-Nan PAN,Jun LU	Predicting Models of Coal Thickness Based on Seismic Attributions and Their Applications	2006	
Ogiesoba OC	Porosity prediction from seismic attributes of the Ordovician Trenton-Black River groups, Rochester field, southern Ontario	2010	10.1306/04061009020
Brown AR	Interpretation of Three-Dimensional Seismic Data	2011	
Ayolabi EA,Adigun AO	The Use of Seismic Attributes to Enhance Structural Interpretation of Z-Field, Onshore Niger Delta	2013	10.5539/esr.v2n2p223
Marcin P	Seismic Characterization of Geothermal Reservoirs by Application of the Common-Reflection-Surface Method and	2014	
Taner MT	Seismic attributes	2001	
Zhao T,Li F,Marfurt K	Automated input attribute weighting for unsupervised seismic facies analysis	2017	10.1190/segam2017-
Carter DC	Use of Windowed Seismic Attributes in 3D Seismic Facies Analysis and Pattern Recognition	1995	
Liang X,Zhao CD,He Y,Bouchet F,Liu C,Wang L,Li Q	Optimizing Well Design and Real-Time Drilling Operations Using a Seismic Attribute Guided Methodology	2017	10.2118/188746-MS
Sajjad Gharechelou, Ziba Hosseini, Ali Kadkhodaie, Ali Chehrazi	Determination of Asmari Reservoir Pore Types Distribution Using Three-Dimensional Seismic Markers in a Southwest	2017	10.22078 /
Wang S,Li XY,Di B,Booth D	Reservoir fluid substitution effects on seismic profile interpretation: A physical modeling experiment	2010	10.1029/2010GL043090
Miall AD	Stratigraphy: A Modern Synthesis	2016	10.1007/978-3-319-24304-7
Tipton A	Analysis of Two Neighboring Miocene Paleo-Turbidite Systems in a Complex Deep-Water Environment: Implications for	2006	
Zhao W,Forte E,Pipan M,Tian G	Ground Penetrating Radar (GPR) attribute analysis for archaeological prospection	2013	10.1016/j.jappgeo.2013.04.01
Gosse CL	Geostatistical Analysis Of Little Bow Oil Field, Alberta, Canada	1999	
Costa FB	Processing and Interpretation of 2D Seismic Data in the Jequitinhonha Basin	2007	
Vieth KU	Kinematic wavefield attributes in seismic imaging	2001	
Pascoal HN	Characterization and Delimitation of Reservoirs Using Seismic Attributes	2012	
Leginowicz	The analysis of 3D data seismic attributes with use of Petrel system	2011	
Schmalz B,Lennartz B	Analyses of soil water content variations and GPR attribute distributions	2002	10.1016/S0022-
Ehret B	Pattern recognition of geophysical data	2010	10.1016/j.geoderma.2009.09
Chao W,Mian C,Yan J	A prediction method of borehole stability based on seismic attribute technology	2009	10.1016/j.petrol.2008.12.033
Mu YG,Cao SY	Seismic physical modeling and sandstone reservoir detection using absorption coefficients of seismic reflections	2004	10.1016/S0920-
Duchesne MJ,Halliday EJ,Barrie JV	Analyzing seismic imagery in the time–amplitude and time–frequency domains to determine fluid nature and migration	2011	10.1016/j.jappgeo.2010.12.00
Fomel S	Local seismic attributes	2007	10.1190/1.2437573
Xiao C,Tian L,Zhang Y,Hou T,Yang Y,Deng Y,Wang Y,Chen S	A Novel Approach To Detect Interacting Behavior Between Hydraulic Fracture and Natural Fracture by Use of	2017	10.2118/187954-PA
Adriansyah A,McMechan G	Analysis and interpretation of seismic data from thin reservoirs: Northwest Java Basin, Indonesia	2002	10.1190/1.1451317
García SR,Romo MP,Figueroa-Nazuno J	Characterization of ground motions using recurrence plots	2013	10.1016/S0016-
Iturrarán-Viveros U	Smooth regression to estimate effective porosity using seismic attributes	2012	10.1016/j.jappgeo.2011.10.012
Forte E,Pipan M,Casabianca D,Di Cuia R,Riva A	Imaging and characterization of a carbonate hydrocarbon reservoir analogue using GPR attributes	2012	10.1016/j.jappgeo.2011.09.00
Iturrarán-Viveros U,Parra JO	Artificial Neural Networks applied to estimate permeability, porosity and intrinsic attenuation using seismic attributes and	2014	10.1016/j.jappgeo.2014.05.01
Xue Y,Cheng L,Mou J,Zhao W	A new fracture prediction method by combining genetic algorithm with neural network in low-permeability reservoirs	2014	10.1016/j.petrol.2014.06.033
Raef AE,Meek TN,Totten MW	Applications of 3D seismic attribute analysis in hydrocarbon prospect identification and evaluation: Verification and	2016	10.1016/j.marpetgeo.2016.02.
Ansari HR	Use seismic colored inversion and power law committee machine based on imperial competitive algorithm for improving	2014	10.1016/j.jappgeo.2014.06.01
Maleki S,Ramazi HR,Gholami R,Sadeghzadeh F	Application of seismic attributes in structural study and fracture analysis of DQ oil field, Iran	2015	10.1016/j.ejpe.2015.05.001
Li X,Chen Q,Wu C,Liu H,Fang Y	Application of multi-seismic attributes analysis in the study of distributary channels	2016	10.1016/j.marpetgeo.2016.04
Pussak M,Bauer K,Stiller M,Bujakowski W	Improved 3D seismic attribute mapping by CRS stacking instead of NMO stacking: Application to a geothermal reservoir in	2014	10.1016/j.jappgeo.2014.01.02
Shiroodi SK,Ghafoori M,Ansari HR,Lashkaripour G,Ghanadian M	Shear wave prediction using committee fuzzy model constrained by lithofacies, Zagros basin, SW Iran	2017	10.1016/j.jafrearsci.2016.11.01
Yue Y,Wang J	SVM method for predicting the thickness of sandstone	2007	10.1007/s11770-007-0037-4
Jyothi V,Sain K,Pandey V,Bhaumik AK	Seismic attenuation for characterization of gas hydrate reservoir in Krishna-Godavari basin, eastern Indian margin	2017	10.1007/s12594-017-0713-9
Liu XF,Zheng XD,Xu GC,Wang L,Yang H	Locally linear embedding-based seismic attribute extraction and applications	2010	10.1007/s11770-010-0260-2
Minken D,Castagna J	Gas-bearing hydrothermal dolomite prediction using probabilistic neural networks in the Trenton-Black River Interval, NE	2003	10.1190/1.1817948
Dinh H,van der Baan M,Landrø M	Processing and quality-control strategies for consistent time-lapse seismic attributes: A case history on an internal blowout	2017	10.1190/geo2016-0448.1
Kobrunov A,Priezzhev I	Hybrid combination genetic algorithm and controlled gradient method to train a neural network	2016	10.1190/geo2015-0297.1
Wang Y,Eichkitz C,Schreilechner M,Heinemann G,Davis J,Gharsalla	Seismic attributes for description of reef growth and channel system evolution — Case study of Intisar E, Libya	2015	10.1190/INT-2015-0017.1
Xie T,Zheng X,Zhang Y	Seismic facies analysis based on speech recognition feature parameters	2017	10.1190/geo2016-0121.1
Zhao T,Li F,Marfurt K	Seismic attribute selection for unsupervised seismic facies analysis using user-guided data-adaptive weights	2017	10.1190/geo2017-0192.1
Wang Z,Yin C,Lei X,Gu F,Gao J	Joint rough sets and Karhunen-Loève transform approach to seismic attribute selection for porosity prediction in a Chinese	2015	10.1190/INT-2014-0268.1
Gao D,Duan T	Seismic structure and texture analyses for fractured reservoir characterization: An integrated workflow	2017	10.1190/INT-2016-0238.1
Dorrington K,Link C	Genetic algorithm/neural network approach to seismic attribute selection for well log prediction	2004	10.1190/1.1649389

Authors	Title	Publication	DOI
Pramanik A,Singh V,Vig R,Srivastava A,Tiwary D	Estimation of effective porosity using geostatistics and multiattribute transforms: A case study	2004	10.1190/1.1707054
Gao D	Latest developments in seismic texture analysis for subsurface structure, facies, and reservoir characterization: A review	2011	10.1190/1.3553479
Hampson D,Schuelke J,Quirein J	Use of multiattribute transforms to predict log properties from seismic data	2001	10.1190/1.1444899
Tebo JM,Hart BS	Use of Volume-Based 3-D Seismic Attribute Analysis to Characterize Physical-Property Distribution: A Case Study to	2005	10.2110/jsr.2005.058
Ogiesoba O,Hart B	Fault imaging in hydrothermal dolomite reservoirs: A case study	2009	10.1190/1.3106722
Wang CC,Shi ZJ,Sun YB,Wang X,Zhou HL	Quantitative analysis method of seismic attributes under limited well control conditions and its application to source rock	2015	10.1007/s12517-014-1445-4
Wang Z,Gao J,Wang D,Wei Q	3D seismic attributes for a tight gas sand reservoir characterization of the eastern Sulige gas field, Ordos Basin, China	2015	10.1190/geo2014-0362.1
Gharechelou S,Sohrabi S,Kadkhodaie A,Rahimpour-Bonab	A seismic-driven 3D model of rock mechanical facies: An example from the Asmari reservoir, SW Iran	2016	10.1016/j.petrol.2016.08.009
Cao Q,Ye J,Wang W,Shi W,Chen C	Preliminary prediction and evaluation on source rock in low exploration basin—A case study from the northeast depression,	2009	10.1007/s12583-009-0070-
Roden R,Smith T,Sacrey D	Geologic pattern recognition from seismic attributes: Principal component analysis and self-organizing maps	2015	10.1190/INT-2015-0037.1
Orange DL,García-García A,McConnell D,Lorenson T,Fortier	High-resolution Surveys for Geohazards and Shallow Gas: NW Adriatic (Italy) and Iskenderun Bay (Turkey)	2005	10.1007/s11001-005-3722-9
Xu B,Xiao A,Wu L,Mao L,Dong Y,Zhou L	3D seismic attributes for structural analysis in compressional context: A case study from western Sichuan Basin	2014	10.1007/s12583-014-0497-4
Leucci G,Masini N,Persico R	Time–frequency analysis of GPR data to investigate the damage of monumental buildings	2012	10.1088/1742-2132/9/4/S81
Kumar A,Khir MH,Yusoff WI	A model-based approach for integration analysis of well log and seismic data for reservoir characterization	2016	10.1007/s12303-015-0045-y
Azar JH,Nabi-Bidhendi M,Javaherian A,Pishvaie MR	Integrated seismic attributes to characterize a widely distributed carbonate clastic deposit system in Khuzestan Province,	2009	10.1088/1742-2132/6/2/007
Reza Rezaee M,Kadkhodaie-Ilkhchi A,Alizadeh PM	Intelligent approaches for the synthesis of petrophysical logs	2007	10.1088/1742-2132/5/1/002
Athmer W,Gonzalez Uribe GA,Luthi SM,Donselaar ME	Tectonic control on the distribution of Palaeocene marine syn-rift deposits in the Fenris Graben, northwestern Vøring	2011	10.1111/j.1365-
Marroquín ID,Hart BS	Seismic attribute-based characterization of coalbed methane reservoirs: An example from the Fruitland Formation, San	2004	10.1306/05190403088
Jalalalhosseini SM,Ali H,Mostafazadeh M	Predicting Porosity by Using Seismic Multi-Attributes and Well Data and Combining These Available Data by Geostatistical	2014	10.1080/10916466.2011.5841
Zhu W,Wu C,Wang J,Fang Y,Wang C,Chen Q,Liu H	Two-stage evolution of the Cenozoic Kunbei fault system and its control of deposition in the SW Qaidam Basin, China	2017	10.1007/s00531-016-1399-8
Singh Y,Nair RR,Singh H,Datta P,Jaiswal P,Dewangan P,Ramaprasad	Prediction of gas hydrate saturation throughout the seismic section in Krishna Godavari basin using multivariate linear	2016	10.1007/s12517-016-2434-6
Moscardelli L,Wood L	New classification system for mass transport complexes in offshore Trinidad	2008	10.1111/j.1365-
Raef A,Totten M,Vohs A,Linares A	3D Seismic Reflection Amplitude and Instantaneous Frequency Attributes in Mapping Thin Hydrocarbon Reservoir	2017	10.1007/s00024-017-1664-1
Raeesi M,Moradzadeh A,Doulati Ardejani F,Rahimi M	Classification and identification of hydrocarbon reservoir lithofacies and their heterogeneity using seismic attributes, logs	2012	10.1016/j.petrol.2012.01.012
Todorov T	Integration of 3C-3D Seismic Data and Well Logs for Rock Property Estimation	2000	
Chirnos ER	Seismic Characterization of Fractures in Carbonated Reservoirs - Cuenca Ucayali Sur, Camisea Area - Peru	2016	
Sancevero SS	Study of Application of Quantitative Methods in Seismic Data in the Characterization Process Integrated Reservoirs	2007	
Janson X,Kerans C,Loucks R,Marhx MA,Reyes C,Murguia F	Seismic architecture of a Lower Cretaceous platform-to-slope system, Santa Agueda and Poza Rica fields, Mexico	2011	10.1306/06301009107
Kilic CO	Characterization and Quantification of Middle Miocene Reservoirs of Starfak and Tiger Shoal Fields, Offshore Louisiana,	2004	
Das KS	Gas-hydrates Saturation Estimation in Krishna-Godavari Basin, India	2013	
Almoqbel AM	Carbonate Reservoir Characterization Based on Integration of 3-D Seismic Data and Well Logs Using Conventional and	2011	
Sitouah M	Estimation of Reservoir Properties from Seismic Attributes and Well Log Data using Artificial Intelligence	2009	
Jaradat RA	Prediction of Reservoir Properties of the N-Sand, Vermilion Block 50, Gulf of Mexico, From Multivariate Seismic Attributes	2004	
Mocnik A	Processing and Analysis of Seismic Reflection Data for Hydrocarbon Exploration in the Plio-Quaternary Marine Sediments	2011	
Ma YZ,LaPointe PR	Uncertainty Analysis and Reservoir Modeling	2011	
Cordsen A,Galbraith M,Peirce J	Planning Land 3-D Seismic Surveys	2000	10.1190/1.9781560801801
Wang CC,Shi ZJ,Sun YB,Zhou HL	Using joint constraint of pseudo- and real-wells for the prediction of thin-bed thickness	2015	10.1007/s11200-015-0703-6
Jalalalhosseini SM,Eskandari S,Mortezazadeh E	The Technique of Seismic Inversion and Use of the Relation Between Inversion Results and Porosity Log for Predicting	2015	10.1080/15567036.2011.580
Li M,Zhao Y	Geophysical Exploration Technology: Applications in Lithological and Stratigraphic Reservoirs	2014	
Pandey AK,Negi A,Bisht BS,Chaudhuri PK,Kumar R	An Integrated Approach to Delineate Reservoir Facies through Multi Attribute Analysis in Complex Lithological	2015	10.2118/178068-MS
Yang P,Yin X,Zhang G	Seismic Data Analysis Based on Fuzzy Clustering	2006	10.1109/ICOSP.2006.34610
Costa FA,Suarez CR,Sarzenski DJ,Ferreira Guedes CC	Using Seismic Attributes in Petrophysical Reservoir Characterization	2007	10.2118/107935-MS
Fleck E,Santos R	Clustering seismic data: A multivariable approach	2007	10.1190/1.2792898
Arianfar A,Khedri B,Haghighi M,Golalzadeh A,Poladzadeh	Case History: Seismic facies analysis based on 3D multiattribute volume classification in Shadegan Oilfield - Asmari	2007	10.2118/111078-MS
He H,Jin S,Yang W,Zhu X	Apply Study on Evaluation Techniques for Oil Gas Reservoir Based on Neural Networks Techniques	2006	10.1109/WCICA.2006.17128
Pan HY,He H	Evaluation Techniques for Oil Gas Reservoir Based on Artificial Neural Networks Techniques	2010	10.1109/BIFE.2010.17
Umam S	Assessing Horizontal Stress Direction Using Seismic and Borehole Geometry Data: Study from Balam South Field	2005	10.2523/IPTC-10551-MS
Li F,Wang S,Chen X	Multiple attribute fusion based on fuzzy logic in oil-gas prediction	2013	10.1190/segam2013-1037.1
Zhao T,Ramachandran K	Performance evaluation of complex neural networks in reservoir characterization: Applied to Boonsville 3-D seismic data	2013	10.1190/segam2013-0227.1
Kobrunov A,Priezzhev* I	Stable nonlinear predictive operator based on neural network, genetic algorithm and controlled gradient method	2015	10.1190/segam2015-

Authors	Title	Publication	DOI
Taner MT,Schuelke JS,O'Doherty R,Baysal E	Seismic attributes revisited	1994	10.1190/1.1822709
Iske A,Randen T	Mathematical Methods and Modelling in Hydrocarbon Exploration and Production	2004	
Randen T,Sønneland L	Atlas of 3D Seismic Attributes	2005	10.1007/3-540-26493-0_2
Marfurt KJ	Seismic Attributes as the Framework for Data Integration Throughout the Oilfield Life Cycle	2018	10.1190/1.9781560803522
Siliqi R,Talaalout A	Structurally coherent wide azimuth residual move out surfaces	2009	10.1190/1.3255713
Scheevel JR,Payrazyan K	Principal Component Analysis Applied to 3D Seismic Data for Reservoir Property Estimation	1999	10.2118/56734-MS
Barnes AE	Genetic classification of complex seismic trace attributes	1997	
Azevedo L,Pinheiro LM,Kaschaka A,Abbassi H	Characterization of hydrocarbon reservoirs using seismic attributes	2010	
Sheriff RE	Encyclopedic Dictionary of Applied Geophysics	2002	
Busing M	Porosity prediction from seismic data through the use of multi-attribute transformations and artificial neural network	2015	
Praseti IP	Increased Seismic Data Resolution Using Spectral Decomposition Attributes at Canadian Exploration Fields		
Batista LM,Bahia S	Extração de Atributos do Sinal Sísmico Utilizando a Distribuição de Wigner-Ville eo Método de Máxima Entropia		
Castaño Giraldo KP	Distribution of thin layers applying spectral inversion and seismic attributes / Thin-layer detection through spectral	2010	
Hutton AC	Geophysical modeling and structural interpretation of a 3D reflection seismic survey in Farnsworth Unit, TX	2015	
Shuaib ME	Seismic attributes and petrophysical modeling of the Aradeiba-D member, Muglad rift basin, Sudan	2013	
Barnes A	Handbook of Poststack Seismic Attributes	2016	10.1190/1.9781560803324
Essenreiter R	Identification and Attenuation of Multiple Reflections with Neural Networks	1999	
Liner C,Li C,Gersztenkorn A,Smythe J	SPICE: A new general seismic attribute	2004	10.1190/1.1845256
Ojeda GY,García PA,Rubiano JL,Gómez FH,Rojas NA,Restrepo-	Estimation of Net Sand Thickness in Transitional Reservoirs Based on Multi-Attribute Analysis: Barco Formation, Campo	2009	
Chen W,Chen YK	Seismic Response of Weak Reflector Based on a Seismic Physical Model	2016	
Mora C,Biondi B	Seismic attribute sensitivity to velocity uncertainty	2001	
Hong S,Deutsch CV	Data Integration with Direct Multivariate Density Estimation	2008	
Gratwick D,Rosales D	Seismic velocity and attribute study based on well interpolated data	2001	
Todorov T,Hampson D,Russell B	Sonic log predictions using seismic attributes	1997	
Pramanik AG,Painuly PK,Singh V,Katiyar R	Geophysical technology integration in hydrocarbon exploration and production: an overview	2001	
Rana S,Burley SD,Chowdhury S	The application of hierarchical seismic attribute combination to high precision infill well planning in the South Tapti Field,	2006	
Odegard JE,Steeghs P,Baraniuk RG,Burrus CS,et al.	Rice Consortium for Computational Seismic Interpretation	1998	
Barnes AE	Seismic attributes in your facies	2001	
Vasudevan K,Cook FA,Eaton DW	Seismic skeletonization: a useful tool for geophysical data analysis	2006	
Shimanskiy SV	Nonstructural Traps Exploration Method Based on Complex Study of 3D Seismic Data and Lithofacies Analysis	2014	10.3997/2214-
Roden R,Chen CW	Interpretation of DHI characteristics with machine learning	2017	
Dorn GA	Interpreting 3-D Seismic Data	1999	
Yu X,Ma YZ,Psaila D,La Pointe P,Gomez E,Li S	Reservoir characterization and modeling: a look back to see the way forward	2011	
Pacheco BO	Implementation of Algorithms for Feasibility Studies of Seismic Attributes Using Synthetic Data	2005	
Gouverneur AG	Estimation and Modeling of Gas Field Properties from Seismic Attributes and Geostatistics, in Spain	2008	
Barnes A	Redundant and useless seismic attributes	2007	10.1190/1.2716717
Chopra S,Marfurt KJ	Seismic attributes for prospect identification and reservoir characterization	2007	10.1190/1.9781560801900
Chopra S,Marfurt KJ	Seismic attributes — A historical perspective	2005	10.1190/1.2098670
Johnston DH	Methods and applications in reservoir geophysics	2010	
Sheriff RE,Brown AR,Lansley RM	Fundamentals of Reservoir Geophysics	2010	
Herron DA	First Steps in Seismic Interpretation	2011	10.1190/1.9781560802938
Liner C	Chapter 24: Seismic Attributes	2016	10.1190/1.9781560803386.c
Liner C	Elements of 3D Seismology	2016	10.1190/1.9781560803386
dGB Earth Sciences	OpendTect Attributes Matrix	2016	
Brown A	Seismic attributes and their classification	1996	10.1190/1.1437208
Rotimi OJ,Ako BD,Zhenli W	Application of Rock and Seismic Properties for Prediction of Hydrocarbon Potential	2014	
John RO,Aduojo AA,Taiwo AO	Applications of 3-D structural interpretation and seismic attribute analysis to hydrocarbon prospecting over X-field, Niger-	2010	
Wang CC,Shi ZJ,Sun YB,Zhou HL	Using joint constraint of pseudo- and real-wells for the prediction of thin-bed thickness	2015	10.1007/s11200-015-0703-6
Baaske UP,Mutti M,Baioni F,Bertozzi G,Naini MA	Using multi-attribute neural networks classification for seismic carbonate fades mapping: a workflow example from mid-	2007	10.1144/GSL.SP.2007.277.01
Roberts A	Curvature attributes and their application to 3D interpreted horizons	2001	

Authors	Title	Publication	DOI
Mojeddifar S,Kamali G,Ranjbar H,Bavarsad BS	A comparative study between a pseudo-forward equation (PFE) and intelligence methods for the characterization of the	2014	10.22059/IJMGE.2014.53105
Rastegarnia M,Kadkhodaie A	Estimation of flow zone indicator distribution by using seismic data: a case study from a central Iranian oilfield	2013	10.22050/IJOGST.2013.479
Alifudin RF,Lestari W,Syaifuddin F,Wahdanadi Haidar M	Karakterisasi Reservoir Karbonat Dengan Aplikasi Seismik Atribut Dan Inversi Seismik Impedansi Akustik	2016	10.12962/j25023659.v2i2.19
Carrillat A,Hunt D,Randen T,Sonneland L,Elvebakk G	Automated mapping of carbonate build-ups and palaeokarst from the Norwegian Barents Sea using 3D seismic texture	2005	
Rafiq A	Integrated Interpretation of Microseismic with Surface Seismic Data in a Tight Gas Reservoir, Central Alberta, Canada	2015	
Tadesse K	Integrated geophysical data processing and interpretation of crustal structure in Ethiopia with emphasis on the Ogaden	2007	
Greenfield H	Seismic Attributes to Constrain the Distribution of Rakopi Formation Coals in the Southwest Offshore Taranaki Basin, New	2016	
Raef AE,Mattern F,Philip C,Totten MW	3D seismic attributes and well-log facies analysis for prospect identification and evaluation: Interpreted palaeoshoreline	2015	10.1016/j.petrol.2015.04.028
de Castro Nunes BI,Eugênio de Medeiros W,Farias do Nascimento	Estimating quality factor from surface seismic data: A comparison of current approaches	2011	10.1016/j.jappgeo.2011.07.00
Mandal HS,Khan PK,Shukla AK	Shear wave attenuation characteristics over the Central India Tectonic Zone and its surroundings	2013	10.1016/j.jseaes.2013.05.020
Wang H,Ma J,Li L,Jia L,Tan M,Cui S,Zhang Y,Qu Z	Time-lapse Seismic Analysis for Gao89 Area of CO2-EOR Project in SINOPEC Shengli Oilfield, China	2017	10.1016/j.egypro.2017.03.153
Sliz K,Al-Dossary S	Seismic attributes and kinematic azimuthal analysis for fracture and stress detection in complex geologic settings	2014	10.1190/INT-2013-0082.1
Tebo JM,Hart BS	Use of Volume-Based 3-D Seismic Attribute Analysis to Characterize Physical-Property Distribution: A Case Study to	2005	10.2110/jsr.2005.058
Perrin M,Rainaud JF	Shared Earth Modeling: Knowledge Driven Solutions for Building and Managing Subsurface 3D Geological Models	2013	
de Matos MC	Recognition of Seismic Patterns Using Analyzes Time-Frequency	2004	10.17771/pucrio.acad.5081
Gustie PJ	Characterization of VTI media with PS [subscript v] AVO attributes	2014	
Oyeyemi KD,Aizebeokhai AP	Seismic attributes analysis for reservoir characterization; offshore Niger Delta	2015	
Wiley RW,Golden BC,Wilson PH,Peters SW	Using seismic attributes to detect vertical fractures: A physical model study	2008	
Demarco LF,da Fontoura Klein AH,Souza J	Marine substrate response evaluation from seismic attributes: A case study using CHIRP	2015	10.1109/RIOAcoustics.2015.7
Taner MT,Walls J,Taylor G	Seismic Attributes, Their Use in Petrophysical Classification	2001	
Mahapatra SN	Determination of heterogeneity by high-resolution seismic reservoir characterization in the heavy oil temblor reservoir of	2005	
Amendola A,Gabbriellini G,Dell'Aversana P,Marini AJ	Seismic facies analysis through musical attributes	2017	10.1111/1365-2478.12504
Pebrian IP,Hiskiawan P,Arkundato A	Seismic Resolution Enhacement with Spectral Decomposition Attribute at Exploration Field in Canada	2017	
Ruliyanti R,Hiskiawan P,Arkundato A	Instantaneous Analysis Attribute for Reservoir Characterization at Basin Nova-Scotia, Canada	2017	
Bjørlykke K	Petroleum Geoscience: From Sedimentary Environments to Rock Physics	2015	10.1007/978-3-642-34132-8
Verney P	Geological Interpretation of Seismic Data by a Supervised Method Based on Cognitive Vision	2010	
Roepnarain R	Seismic Attribute Analysis of the Upper Cretaceous below the Tambaredjo oil field, Suriname	2013	
Karlzen K	Cenomanian to Eocene Stratigraphy of the Jeanne d'Arc Basin Offshore Newfoundland, Canada, with Detailed	2017	
Li G	3D Seismic Attributes Enhancement and Detection by Advanced Technology of Image Analysis	2012	
Awosemo OO	Evaluation of elastic impedance attributes in offshore High Island, Gulf of Mexico	2012	
A ?حر لاأن?سح إيكم إيلع M. Al-Rahim	Enhancing the indication of ancient geologic features by using Seismic Attributes technique extracted along picked	2015	
Aliani A	3D Mapping of Mesozoic Fault Systems and Horizons using Reflection Seismic Volume from Kristin Field	2015	
Sugiri OI	FRACTURED BASEMENT DELINEATION USING SEISMIC MULTI-ATTRIBUTES: THE MLB FIELD, JAMBI, INDONESIA	2010	
Marfurt K	Techniques and best practices in multiattribute display	2015	10.1190/INT-2014-0133.1
Gersztenkorn A	A Wavelet Based Attribute for Detection of Stratigraphic and Structural Frameworks	2005	
Orlando L,Contini P,De Girolamo P	Seismic scattering attribute for sedimentary classification of nearshore marine quarries for a major beach nourishment	2017	10.1016/j.jappgeo.2017.04.0
Yuan Y,Liu Y,Zhang J,Wei X,Chen T	Reservoir prediction using multi-wave seismic attributes	2011	10.1007/s11589-011-0800-8
Lambert MA,Schmalholz SM,Saenger EH,Steiner B	Reply to comment on 'Low-frequency microtremor anomalies at an oil and gas field in Voitsdorf, Austria' by Marc-André	2010	10.1111/j.1365-
Ruiz Cardona MC	Lithostratigraphic characterization of the La Luna Formation through the analysis of seismic multiatributes in the	2013	
Ulrych T,Sacchi M,Graul M,Taner MT	Instantaneous attributes: the what and the how	2007	
Taner MT	Seismic Attributes, Their Classification And Projected Utilization	1999	
Walls JD,Taner MT,Taylor G,Smith M,Carr M,Derzhi N,Drummond	Seismic reservoir characterization of a mid-continent fluvial system using rock physics, poststack seismic attributes and	2000	
	Seismic reservoir characterization of a U.S. Midcontinent fluvial system using rock physics, poststack seismic attributes, and	2002	10.1190/1.1481248
Misra AA,Mukherjee S	Atlas of Structural Geological Interpretation from Seismic Images	2018	
Mancini EA	Integrated Geologic-Engineering Model for Reef and Carbonate Shoal Reservoirs Associated with Paleohighs: Upper	2003	
Schuelke JS,Quirein JA,Sag JF,Altany DA,Hunt PE	Reservoir architecture and porosity distribution, Pegasus Field, West Texas—An integrated sequence stratigraphic-seismic	1997	
Walls JD,Taner MT,Guidish T,Taylor G,Dumas D,Derzhi N	North Sea reservoir characterization using rock physics, seismic attributes, and neural networks; a case history	1999	
Karimi P,Fomel S	Image guided well log interpolation using predictive painting	2015	10.1190/segam2015-
Bagheri M,Riahi MA,Hashemi H	Reservoir lithofacies analysis using 3D seismic data in dissimilarity space	2013	10.1088/1742-
Vasudevan K,Cook FA	Time-frequency analysis of deep crustal reflection seismic data using Wigner-Ville distributions	2001	10.1139/cjes-38-7-1027

Authors	Title	Publication	DOI
Kılıç CO	Characterization and Quantification of Middle Miocene Reservoirs of Starfak and Tiger Shoal Fields, Offshore Louisiana,	2004	
Hashemi H,Tax DM,Duin RP,Javaherian A,de Groot P	Gas chimney detection based on improving the performance of combined multilayer perceptron and support vector	2008	10.5194/npg-15-863-2008
Gharehlo AM	Development of Artificial Expert Reservoir Characterization Tools for Unconventional Reservoirs	2012	
Jibrin B	Relations between fault surface morphology and volume structure: 3-D seismic attribute analysis deepwater Niger Delta	2012	
		2002	
A H,M Z,A KR,A R,R G,J H	Artificial Intelligence for prediction of porosity from Seismic Attributes: Case study in the Persian Gulf	2011	
Langdon CB	An Integrated Analysis Of The Oppliger and Harkness Oil Fields Using Well Log Data and 3D Seismic Data	2016	
Walls JD,Taner MT,Guidish T,Taylor G,Dumas D,Derzhi N	North Sea reservoir characterization using rock physics, seismic attributes, and neural networks; a case history	1999	10.1190/1.1820825
McBride J,William Keach R,Wolfe E,Leetaru H,Chandler	Investigating fault continuity associated with geologic carbon storage planning in the Illinois Basin	2014	10.1190/INT-2013-0109.1
Wang B,Pann K,Schuelke J,Shirley T,Ferguson B	View of neural network training as constrained optimization and applications to rock porosity prediction	1997	10.1190/1.1886143
Fouad K,Ambrose WA,Brown F	Seismic facies and attribute analysis of the Miocene incised-valley-fill and submarine-canyon systems in Tuxpan Basin,		
Fouad K,Ambrose WA,Sakurai S,Jennette D,Park YJ	Wave-shape classification and attribute analysis of the lower Miocene deep-water reservoirs, Laguna Madre Basin, offshore		
Iturrarán-Viveros U,de Ciencias F,Parra J	Permeability and porosity from integrated multiattributes and well log data using Smooth regression: Application to a	2013	10.1190/segam2013-0376.1
Adams D,Markus D	Systematic error in instantaneous attributes	2013	10.1190/segam2013-1081.1
Parra J,Iturrarán-Viveros U,Parra J	A workflow using self-organized mapping to predict rock properties from seismic-reflection data	2016	10.1190/segam2016-
Xing L,Aarre V,Barnes A,Theoharis T,Salman N,Tjåland E	Instantaneous Frequency Seismic Attribute Benchmarking	2017	10.1190/segam2017-
Geletti R,Del Ben A,Busetti M,Ramella R,Volpi V	Gas seeps linked to salt structures in the Central Adriatic Sea	2008	10.1111/j.1365-
Alsadi HN	Seismic Hydrocarbon Exploration: 2D and 3D Techniques	2016	
Celik U	Neural Network Applications Attributes for Predicting Production and Mapping Fault Zones	2012	
Zou K	Full-Wave Attributes for Multicomponent Data Interpretation	2005	
Raza MA,Yusoff WI	Delineation of Petroleum System Using Faults and Associated Gas Chimneys	2012	10.3997/2214-
Saggaf MM,Toksoz MN,Mustafa HM	Application of Smooth Neural Networks for Inter-Well Estimation of Porosity from Seismic Data	2000	
Maestrelli D,Iacopini D,Jihad AA,Bond CE,Bonini M	Seismic and structural characterization of fluid escape pipes using 3D and partial stack seismic from the Loyal Field	2017	10.1016/j.marpetgeo.2017.08.
Schmelzbach C,Greenhalgh S,Reiser F,Girard JF,Bretaudeau	Advanced seismic processing/imaging techniques and their potential for geothermal exploration	2016	10.1190/INT-2016-0017.1
Walls JD,Taner MT,Taylor G,Smith M,Carr M,Derzhi N,Drummond	Seismic reservoir characterization of a mid continent fluvial system using rock physics, poststack seismic attributes and	2000	10.1190/1.1815674
Salguero-Hernández E,Urrutia-Fucugauchi J,Ramírez-Cruz L	Fracturing and deformation in the Chicxulub crater-Complex trace analysis of instantaneous seismic attributes	2010	
Chen T	Integrated Reservoir Characterization in Delhi Field	2018	
Eichkitz C,Amtmann J,Schreilechner MG	Online Seismic Attribute Database for Efficient Literature Research	2013	10.3997/2214-
Amtmann J,G. Eichkitz C,G. Schreilechner M	Seismic Attribute Database for Time Effective Literature Research	2012	10.3997/2214-
Gholami R,Moradzadeh A,Rasouli V,Hanachi J	Shear wave velocity prediction using seismic attributes and well log data	2014	10.2478/s11600-013-0200-7
	A case study of stratigraphic and lithologic interpretation of thin reservoirs through an integrated approach	2004	10.1190/1.1813354
Khan KA,Akhter G	Review of instantaneous, wavelet, and weighted seismic attributes along with a computational library	2015	10.1007/s12517-015-2044-8
Yuan Y,Liu Y,Zhang J,Wei X,Chen T	Reservoir prediction using multi-wave seismic attributes	2011	10.1007/s11589-011-0800-8
Aguiar L,Freire AF,Santos LA	Análise de Atributos na Identificação de Feições Sísmicas Associadas À Presença De Hidratos de Gás Na Bacia da Foz do	2017	10.13140/RG.2.2.18209.254
Sadat MM,Reza RH,Reza BM,Haleh R	Integration of seismic markers and neural networks to identify fault systems in the Strait of Hormuz	2015	

Table A-1: Data used for citation analysis. Table of pertinent data that we used in the review and citation analysis.

Table A-2: Publications not included in citations analysis

Authors	Title	Year
陈开远, 刘学峰, 杜宁平, 黄春菊, 杨玉金	新港地区沙三段三维地震层序地层特征	2000
荒戸裕之, 高橋明久	貯留岩分布予測における地質モデルの役割	2001
张军华, 王永刚, 赵勇, 马永利, 侯伯刚	相干体技术算法改进及其在 TJH 地区的应用	2002
孔炜, 杨瑞召, 彭苏萍	地震多属性分析在煤田拟声波三维数据体预测中的应用	2003
刘振峰, 郝天珧, 王峰, 徐亚	地震资料在层序地层学中的应用进展	2003
杨占龙, 郭精义, 陈启林, 黄云铎	地震信息多参数综合分析与岩性油气藏勘探	2004
崔若飞, 武旭仁, 陈同俊	煤矿地震数据管理系统的开发	2005
卢宝坤, 史謌	测井资料与地震属性关系研究综述	2005
云美厚, 丁伟, 王新红	地震水平分辨力研究与应用	2005
隗寿东	地震属性	2006
高橋明久, 柏原功治, 溝畑茂治, 島田信仁, 中山徹...	オイルサンド貯留層三次元地質モデルの構築	2006
高野修, 荒戸裕之, 中西健史, 松岡俊文, 佐伯龍男	三次元反射法地震探査技術の進展がもたらす地質学, とくに堆積学分野へのインパクト	2006
刘延莉, 樊太亮, 邱春光	岩性地层圈闭研究综述	2006
刘伟方, 段永华, 高建虎, 张喜梅, 孙勤华	利用地震属性预测碳酸盐岩储层	2007
刘春慧, 金振奎, 刘家铎, 王铮, 朱桂芳	地震数据处理技术在准噶尔盆地东部 C25 井西区砂体识别中的应用	2007
蒲仁海, 翟晓先, 严华, 钟红利, 朱李	塔河油田典型地震相	2007
何敏, 施和生	珠江口盆地东部 HZ21-1 气藏及其外围储集体一体化研究	2007
郭华军, 刘庆成	地震属性技术的历史, 现状及发展趋势	2008
石明, 张赛民	地震属性提取及微机上迅速编程实现	2008
曹向阳, 常旭, 刘伊克, 张金淼	奇异性分析方法在地震资料解释及反演研究中的应用	2008
阳孝法, 张学伟, 林畅松	地震地貌学研究新进展	2008
陈冬, 王彦春, 张小波	地震属性分析和应用	2008
齐龙瑜, 胡学鹏, 乔玉雷, 胡北来	基于多地震属性的高分辨率拟测井参数的预测	2008
曹强, 叶加仁, 石万忠, 陈春峰	低勘探程度盆地烃源岩早期评价——以南黄海北部盆地东北凹为例	2009
唐小彪	基于对应分析的支持向量机回归在地震储层厚度预测中的应用	2009
张伟, 王海, 李洪臣, 王彦春, 段云卿	用变换时窗统计能量比法拾取地震初至波	2009
孟召平, 郭彦省, 马辉	应用地震属性预测煤层顶板泥岩百分比含量分布 Prediction of Mudstone Percentage Content for Coal Roof	2009
阳飞舟, 崔永福, 李青	地震属性分类及其应用	2009
刘朋波, 蒲仁海, 刘娟霞	十屋断陷火石岭组–营城组沉积微相研究与储层识别	2009
赖维成, 宋章强, 周心怀, 李建平, 滕玉波, 沈章洪	地质一地震储层预测技术及其在渤海海域的应用	2009
张义娜, 朱筱敏, 刘长利	地震沉积学及其在中亚南部地区的应用	2009
宋章强, 赖维成, 牛成民, 薛金宝, 沈洪涛, 于圣杰	渤海海域湖相碳酸盐岩地震-地质综合预测方法及应用	2009
王雪峰, 李忠权, 蒙启安, 朱德丰, 杭文燕, 陈均亮	构造因素对地震剖面视频率的影响——以海拉尔盆地乌尔逊凹陷为例	2010
卫平生, 潘建国, 张虎权, 谭开俊	地震储层学的概念, 研究方法和关键技术	2010
王建功, 卫平生, 王天琦	碎屑岩地震储层学的内涵及关键技术	2010
白仲才	地震属性分析在秧坝凹陷上二叠统沉积相研究中的应用	2010
袁野, 刘洋	地震属性优化与预测新进展	2010
袁野, 刘洋	地震属性优化与预测新进展	2010
赵亮, 赵春霞, 张二华	三维地震体数据方向场估计算法	2010
王军, 周东红, 张中巧, 郑敬贵, 石文龙, 张海义	低位楔形三角洲砂体岩性尖灭线地震响应特征探索	2010
高建荣, 郭彦如, 徐旺林	地层等时格架技术	2010
刘朋波, 蒲仁海, 刘娟霞	松辽盆地十屋断陷前积反射特征及意义	2010
吴因业, 张天舒, 张志杰, 崔化娟	沉积体系域类型, 特征及石油地质意义	2010
陈常乐, 刘洋, 刘财, 汪春江	局部地震属性识别火山岩体	2011
崔大尉, 王一, 田庆路, 刘最亮, 齐振洪	利用地震属性解释煤层冲刷带	2011
朱超, 宫清顺, 孟祥超, 金科年	地震属性分析在扇体识别中的应用	2011
华岗, 刘芳, 林海, 孙劲光	地震数据的多属性三边滤波算法	2011
华岗, 陶煜波, 林海	鲁棒多尺度地震层位识别与可视化	2011
ВН Смирнов	ПОДХОД К ОЦЕНКЕ ПЕРЕМЕННОГО ПО ЛАТЕРАЛИ СЕЙСМИЧЕСКОГО СИГНАЛА ПО СКВАЖИННЫМ И	2011
张广旭, 吴时国, 朱伟林, 施和生, 陈端新	南海北部陆坡流花碳酸盐台地地球物理响应	2011

Authors	Title	Year
段如泰, 金振奎, 杨婷, 索重辉, 潘怡	地震沉积学研究中的方法和技术	2011
蒲仁海, 党晓红, 许璟, 伊红佳	塔里木盆地二叠系划分对比与火山岩分布	2011
郭倩, 蒲仁海, 杨林, 孙国峰, 朱李, 楚宪波	塔里木盆地塔河地区志留系上倾尖灭圈闭油气成藏	2011
李建青, 蒲仁海, 武岳, 田媛媛	江苏黄桥地区龙潭组沉积相与有利储层预测	2012
夏义平, 徐礼贵, 温铁民, 张延庆, 王贵重	叠前偏移及储层预测技术研发进展与应用	2012
张佳佳, 李宏兵, 姚逢昌	油页岩的地球物理识别和评价方法	2012
王伟锋, 高斌, 卫平生, 潘建国, 李飞...	火山岩油气藏地球物理预测技术及准噶尔勘探实例	2012
尹成, 王治国	明确地质含义的地震准属性的回顾与探讨	2012
吴斌, 唐洪, 王素荣, 王兴志, 徐立明, 徐正华	利用蚁群算法识别及预测碳酸盐岩裂缝的方法探讨	2012
宁媛丽, 韩立国, 周子阳, 倪冬梅, 吕寅寅	应用反演谱分解去除调谐效应的分频 AVO 技术	2012
刘豪, 周心怀, 田立新, 赖维成, 郭涛, 李世燕, 张帅	高频层序格架下的地质地球物理模型与砂体预测	2012
정순홍, 김병엽, 배재유	캐나다 아퀴스토어 CCS 프로젝트의 이산화탄소 모니터링을 위한 Baseline 탄성파 속성분석	2013
卫平生, 潘建国, 张虎权, 王宏斌, 曲永强, 谭开俊...	石油地震储层研究及应用——以塔里木盆地塔中地区碳酸盐岩为例	2013
吴建军, 杨培杰, 王长江	地震多属性非线性反演方法在东营三角洲中的应用	2013
高磊, 明君, 闫涛, 赵海峰, 李宾	地震属性综合分析技术在泥岩隔夹层识别中的应用	2013
王海峰, 冯云发, 薛建勤, 张梦千, 申玉山, 周游...	柴达木盆地冷湖四号构造 E1+ 2 有利储层预测	2013
柳琼瑶, 吴朝东, 胡天跃, 莫午零, 张顺...	松辽盆地茂兴地区滑塌扇地震属性识别与沉积学分析	2014
范雯	逐步回归分析方法在储层参数预测中的应用 Application of stepwise regression analysis method in reservoir	2014
汪勇, 陈学国, 王月蕾, 桂志先	叠后多属性分析在哈山西石炭系火山岩裂缝预测中的应用研究	2014
程玉红, 马新民, 雍学善, 刘小梅, 倪祥龙	GeoEast 地震属性技术在东坪地区地震综合解释中的应用	2014
汪勇, 陈学国, 王月蕾, 桂志先	叠后多属性分析在哈山西石炭系火山岩裂缝预测中的应用研究	2014
R Gholami, A Moradzadeh, V Rasouli, J Hanachi	Shear wave velocity prediction using seismic attributes and well log data	2014
张宪国, 张涛, 林承焰, 袁辉, 晁彩霞, 张守秀	珠江口盆地文昌 13-1 油田 ZJ2-1U 砂组沉积微相地震刻画	2014
赖生华, 梁全胜, 曾洪流, 李鹏飞	煤层对砂岩地震反射特征的影响及其地震岩性学意义—以鄂尔多斯盆地山 2 段为例	2015
李文鹏, 张二华	基于结构张量的三维地震数据分析	2016
朱红涛, 徐长贵, 朱筱敏, 曾洪流, 姜在兴...	陆相盆地源—汇系统要素耦合研究进展	2017
درفـایرد?ح‌اپیدمحا,?تادخدکـاپیدها,هدازایدبع	یروصنما?تفناناد?مارداناگچرروما?تلکـایزاسهن?هباشورزااهدافتساابایاهزرلا	
A Takahashi, K Kashihara	マルチアトリビュート解析を用いたオイルサンド貯留層の評価	
T MATSUOKA	地圏環境資源研究における物理探査の役割	
刘振峰	油气地震地质模型述评	

Table A-2: Data not used for citation analysis. Table of pertinent data that we lacked time or resources to translate properly for inclusion in the citation analysis.

Chapter 3: Spectral Similarity Fault Enhancement

Fault interpretation of seismic data is a critical task that must be completed to understand the structural history of the subsurface thoroughly. The development of similarity-based attributes has allowed geoscientists to filter a seismic data set to highlight discontinuities that are often associated with fault systems effectively. Furthermore, there are numerous workflows that provide, to varying degrees, the ability to enhance this seismic attribute family. We have developed a new method, spectral similarity, to improve the similarity enhancement by integrating spectral decomposition, swarm intelligence, magnitude filtering, and orientated smoothing. In addition, the spectral similarity method has the ability to take any seismic attribute (e.g., similarity, curvature, total energy, coherent energy gradient, reflector rotation, etc.), combine it with the benefits of spectral decomposition, and create an additional enhancement. The final result is an increase in the quality of the similarity enhancement over previously used methods, and it can be computed entirely in commercial software packages. Specifically, the spectral similarity method provides a more realistic fault dip, reduction of noise, and removal of the discontinuous "stair-step" pattern common to similarity volumes.

Introduction

The application of seismic attributes to fault identification originates from work by Bahorich and Farmer (1995) through the development of the coherence algorithm (crosscorrelation of adjacent seismic traces), which resulted in great efficiency gains by seismic interpreters. However, the early coherence attribute performed poorly in high-noise data sets. The second-generation similarity algorithm, based on multi-trace semblance, has less noise sensitivity (Marfurt et al., 1998). A major drawback to these methods is the sensitivity to amplitude discontinuities. Garsztenkorn and Marfurt (1999) propose a third-generation similarity algorithm computed through the calculation of the eigenvalues of a covariance matrix over a window of seismic data, which removed the amplitude sensitivity while increasing and localizing the fault response on the seismic data. Improvements to dip estimation quickly followed through the development of the dip scan method, which provides superior accuracy and precision to dip estimates in seismic data (Marfurt, 2006). Numerous edge detection algorithms followed, including the introduction of the Sobel filter to seismic data by Aqrawi and Boe (2011).

Soon after the development of edge detection algorithms, came the concept of computer-based fault interpretation. In 2001, similarity attributes were used for computer-based fault extraction, and it was quickly identified that "conditioning" or enhancement of the similarity attribute would be a major and critical step (Randen et al., 2001). The idea of similarity enhancement directly led to the application of ant colony optimization to fault extraction, causing a major step forward for the industry (Pedersen et al., 2002). Nonetheless, Aqrawi and Boe (2011) make the very specific point several years later, "[a]utomatic fault detection and extraction is still considered to be a major challenge for the industry." In an attempt to address this same problem, Dorn et al. (2012) develop the fault-enhanced attribute (also called AFE). Although independent of the swarm intelligence methods proposed by Pedersen et al. (2002), it was an equal step forward in thinking for the industry.

One of the key tasks in seismic interpretation is the identification of faults, and the efficiency gains that are possible through computer-based fault extraction are enormous. Unfortunately, the similarity attributes described earlier are known for poor vertical resolution and are more often used through horizontal slices or horizon extraction based interpretation. This results in poor computer extractions. The major goal of similarity enhancement is to improve the vertical axis response of the similarity volume and the computer-based fault interpretations. We propose a new method for enhancing the similarity volume, spectral similarity, which produces a volume that increases the efficiency of fault interpretation several times over traditional human-based fault interpretation and computer-based fault extraction techniques (Figure 1).

Definitions

Key terms for this paper include the following:

- Similarity is a family of edge detection attributes that include coherence, variance, the Sobel filter, or similar algorithms.
- Swarm intelligence is a family of algorithms that use decentralized self-organization to perform a task (examples include particle swarm optimization, ant colony optimization, or differential evolution).
- Machine learning is a subdiscipline of computer science that consists of algorithms that can learn from and make predictions on data (examples include artificial neural networks, self-organized maps, and k-means clustering).
- Spectral similarity refers to the workflow described in this paper for similarity enhancement.

Motivation

Above, we mention two major steps forward in the enhancement of similarity volumes by Pedersen et al. (2002) and Dorn et al. (2012). Both of these approaches provide a unique look at fault enhancement, which produces very different results. As we will discuss, spectral similarity draws from these ideas with the aim of improving upon them. Both of these methods perform well in many situations. However, we will focus on their respective weaknesses because they perform poorly in similar situations and our goal is to improve upon those specific weaknesses.

The Pedersen et al. (2002) similarity enhancement uses the ant colony optimization technique (a swarm intelligence algorithm) to connect discontinuous similarity events and remove the common stair-step anomaly seen in many similarity-based attributes. This algorithm excels at fault connectivity and the retention of appropriate fault dip. However, this technique is very sensitive to noise and is not generally appropriate for any but the largest faults (Figure 3.2a). Aqrawi and Boe (2011) attempt to improve the results of this swarm intelligence technique by improving the underlying similarity attribute by changing from a semblance-based to a Sobel filter-based attribute. Although this improved the results significantly, the inherent sensitivity of ant colony techniques (and likely all swarm intelligence algorithms) to noise is significant.

The Dorn et al. (2012) AFE is a seismic attribute centered on user-driven filtering of the similarity magnitude combined with an orientated smoothing parameter (Figure 3.2b). This technique excels in the detection of large faults, and, owing to the smoothing parameters, provides excellent fault connectivity in those situations.

However, the technique suffers from poor performance in the presence of small- to medium-sized faults and lacks a method of interpolation to increase fault connectivity.

The vast majority of similarity enhancement techniques (including those mentioned above) commonly suffer from three major classes of detection issues (although not every method suffers from all classes). The first is an abundance of near-vertical similarity response — an effect likely related to either the algorithm or the underlying similarity attribute (see the solid rectangles in Figure 3.2). The second is the inherited stair-step anomaly that is a common effect seen in the underlying similarity volume (see the dotted rectangles in Figure 3.2). Third, many faults are realistically oriented, but they appear broken and discontinuous (see the dashed rectangles in Figure 3.2). It is these three classes of similarity enhancement problems that we are attempting to improve through our proposed spectral similarity attribute workflow.

Spectral Similarity

As shown in Figure 3.2c, spectral similarity improves upon all three classes of problems discussed above. Spectral similarity results in fault dips that are in general agreement with the expectations by area experts and structural geologists, the removal of stair-step errors, and greatly improved fault connectivity. In addition, the range of values (represented by the change in fault colors from light gray to black) implies a confidence or probability in the volume. In practice, this attribute, when used with a computer-based fault interpretation technique, can be further filtered by this confidence to yield very realistic fault surfaces.

As discussed below, we begin with spectral decomposition; therefore, each attribute parameter and filter is customized to a given frequency band. Our technique is, therefore, highly adaptable to a range of data sets. For example, when computing a similarity volume, one key input is the vertical window height, which ideally is a function of the dominant wavelength of the interval of interest. This results in suboptimal parametrization in all areas with different dominant wavelengths (which can vary laterally and vertically). However, in a spectral volume, the optimal window height represents the dominant wavelength of the entire volume. In this work, the lateral windows are kept constant and the vertical window varies (kept to half of the wavelength). If a data set has significant frequency contrasts between the shallow and deep section (e.g., sub-salt Gulf of Mexico), one can create a spectral similarity with frequency components for a shallow section that are drastically different from for the deeper section. Another beneficial feature of spectral similarity is the ability to incorporate any attribute type into the process (e.g., dip magnitude, curvature, reflector rotation, etc.). It is precisely this customizable feature that allows spectral similarity to excel in every data set and basin in which it was applied (regardless of differences in geology).

Workflow Description

The general form of our workflow is independent of specific techniques or approaches (Figure 3.3). The spectral similarity workflow provides a great deal of customization based on individual preferences, data quality, and time constraints. Therefore, it is not possible to define the exact workflow for any given data set or project, but the optimal customized algorithm is quickly identified when constraints (data or time) are applied.

We begin with a seismic data set that is filtered, as needed, for attribute analysis. Then we follow with spectral decomposition (e.g., short-time Fourier transform, continuous wavelet transform [CWT], matching pursuit, crosscorrelation, or constrained least-squares spectral analysis; Figure 3.3a). These band-limited volumes (i.e., spectral voice or similar) are used to compute the seismic attributes (Figure 3.3b). Our experience indicates that higher frequencies (greater than 30 Hz) are more beneficial than are low frequencies (less than 15 Hz), but this is data dependent. We commonly use geometric attributes calculated from these data; however, this workflow can be adopted to use other derivative volumes (e.g., the spectral phase) directly by skipping the attribute generation step and applying the swarm intelligence-based attribute to these volumes directly. Applications of spectral phase for fault identification trace their roots back to 1999 (Partyka et al.). Numerous frequency-based attributes are used as input to swarm intelligence for lineament connection and interpolation between discontinuous events (Figure 3.3c). In the final portion of the workflow, we use each of these swam intelligence volumes as an input into edge-filtering and smoothing operations. We then combine each of these spectral fault-enhanced volumes through addition, resulting in a similarity that has been enhanced through the inclusion of spectral decomposition (Figure 3d). An alternative method to combine the various volumes is through a machine-learning algorithm (in our tests, we used a self-organized map), a technique adapted from Basir et al. (2013). This adds additional computation time, but it significantly reduces the amount of intermediate data volumes created (Figure 3.4 shows the results of this optional approach).

Workflow Customization

It is common for individuals to have preferences and biases to particular algorithms. This is why we present the spectral similarity algorithm in generic terms. The optimum spectral decomposition or similarity method will vary depending on the data specifics. Moreover, individual biases or company policy may further constrain algorithms (e.g., if corporate policy maintains the use of only Sobel filter similarity). In addition, some algorithms and implementations take considerably longer to compute than do others. Therefore, when time constraints, personal/corporate bias, and data-dependent, goal-based constraints are applied, the ideal workflow for a given project is easily identified.

Case Study #1: High Signal-to-Noise

The first data set chosen to illustrate our method is from central Texas, USA. In general, this area is an extensional regime, with normal faults striking approximately perpendicular to the extension direction. However, the underlying structure of the region and vertical stratigraphic variations have influenced the deformation patterns in this package, resulting in multiple fault orientation trends and detachment levels. A paleo-reef is a prominent feature along which many faults nucleate and terminate, creating a fault trend that is oblique to the regional paleo-stress field (Figure 3.5, Figure 3.6C). In addition, early movement of the underlying salt created local variations in the stress regime that affected later faulting (Figure 3.6B and 3.6D). Owing to the local and regional paleo-stresses, we expect the fault patterns to be dominated by normal faults, with orientations that very laterally. The data set is of excellent quality with minimal noise. The notable exception to this is the relatively low signal-to-noise area (Figure 3.6A).

Customized Workflow

We began with a crosscorrelation-based spectral decomposition (Gao, 2013). This type of spectral decomposition is acceptable for geometric interpretation, and the computation time is shorter than for other methods. We used three volumes at approximately 20, 37, and 43 Hz to compute a modified eigenstructure similarity for each spectral volume (Garsztenkorn and Marfurt, 1999). When calculating dip, we used a dip-scan method with a maximum of 30° and an increment of 2° (Marfurt, 2006). We followed with swarm intelligence described by Pedersen et al. (2002), and a Radon transform based filtering and smoothing operation (Dorn et. al., 2012) on each frequency volume. Finally, we added the three frequency-based attribute volumes together. The total size of the original seismic is approximately 17 GB, and the total size of all intermediate volumes, parameter tests, software projects, duplicated data, and SEGY exports is 969 GB. Most of these data were intermediate scratch data that were not retained.

Discussion and Results

To evaluate the quality of the resultant spectral similarity, we asked two dozen structural and geophysical experts (with an average of 17 years of experience, knowledge of multiple basins, and several Ph.D. holders) to compare our results to a traditional similarity volume. The response was a preference among all geoscientists for the spectral similarity algorithm (approximately 96% favorable).

Figure 3.6 illustrates two fault enhancements to the similarity volume—the fault-enhanced volume (Dorn et al., 2012) and spectral similarity discussed in this paper. The quality of the enhancement varies laterally, owing to zones of relatively poor signal to noise and changes in peak frequency. The spectral similarity contains more distinct fault patterns and interactions than the fault-enhanced volume. Specifically, the spectral similarity volume (Figure 3.6b) performs very well in area A, where a large fault zone significantly reduces the signal-to-noise ratio (S/N). Areas B and D have significantly improved fault connectivity in the spectral similarity volume and provide an excellent guide for fault interpretation and refinement of existing fault surfaces. In addition, the increased range of values of the data yields an implied level of confidence directly from the data volume. The darker faults are more pronounced in the spectral similarity method than in the fault-enhanced method, whereas the lighter colors may be smaller faults or even an artifact (i.e., the fault shadow expression commonly seen in time-migrated data). Differences between the fault-enhanced and the spectral similarity method are also visible in the vertical section (Figure 3.7a). The fault-enhanced method commonly results in fault dips that are nearly vertical, whereas the spectral similarity method results in faults that are dipping at moderate angles (Figure 3.7b).

The ultimate goal of any similarity product is to aid in interpretation. Figure3.8 shows the spectral similarity co-rendered with the seismic amplitude, illustrating how an interpreter can use both products for manual or computer-based interpretation. Preexisting faults can also be refined by using spectral similarity for quality control. The noticeable increase in the sharpness of the fault response combined with the range of values of the data volume implies that computer-based fault extraction techniques would perform very well with the spectral similarity attribute.

To investigate the validity of the features identified by spectral similarity, we extracted faults over a short time interval using a data range cutoff and enforcing a strict lower limit to the number of points clustered (via k-means clustering) to 10,000. We extracted 332 total fault planes, which were then checked for quality by a Ph.D. structural geologist with experience in this basin. It was determined that 33% of the faults (108) required no editing, 63% of the faults (209) required only basic editing, and the remaining 4% (15) required editing of the 3D mesh (the software incorrectly connected the points). Moreover, “basic editing” consisted of splitting (dominantly in the vertical direction) the correctly placed points that were clustered together to make larger fault planes. These results are shown in Figure 3.9. Our initial constraints, specifically the number of points required per cluster, were overly conservative, as indicated by the number of readily identifiable faults left uninterpreted. These faults were, in fact, interpreted by the computer, but their cluster sizes were below our 10,000-point lower bound. In the authors’ experience, the faults extracted from previous similarity attributes (and enhanced versions) require more significant editing, and the spectral similarity attribute greatly increases the efficiency of fault interpretation over traditional computer-based fault extraction workflows. In fault extraction comparisons, conducted by the same Ph.D. structural geologist, similar numbers of faults were interpreted by the computer, but the extracted surfaces were overly vertical and required significantly more complex and time-consuming point editing. Using an average elapsed time over 20 fault edits from faults extracted on the spectral similarity attribute and commercially available similarity enhancements, we estimate an increase in human productivity of 6x–8x (the computation time is not accounted for).

In addition to fault surface interpretation, the spectral similarity attribute can provide a clear way to understand and communicate geologic complexity through multiattribute analysis and display. By combining this structural attribute with the peak frequency and peak magnitude from spectral decomposition, we can display the structural grain from the spectral similarity and the lateral lithologic variation as interpreted from the peak frequency and peak magnitude volumes (Figure 3.10). In this case, the low signal-to-noise zone in the lower center of the image is easily identifiable, while still displaying the major fault trends in this area. These faults were later confirmed through quality control and manual interpretation of the amplitude volume by basin experts. Many faults act as boundaries to the peak frequency, whereas other similar faults do not. This type of information may be beneficial to well planning and well placement in various reservoirs.

Case Study #2: Low Signal-to-Noise

Similar to case study no. 1, the area for case study no. 2 is in an extensional regime, with normal faults striking approximately perpendicular to the extensional direction. Basement structures and salt movement have influenced the deposition and deformation patterns of the study area. Movement on a basement fault was accommodated by a series of faults oblique to the regional extension direction (Figures 3.11 and 3.12 rectangle). In addition, salt movement in the northeast area of the study area created local variations from the regional stress regime that influenced fault orientations (Figure 3.11, rectangle).

Customized Workflow

In contrast to case study no. 1, this data set is heavily contaminated by noise (Figure 3.11, left side). Therefore, as a first step, we applied a series of progressively larger windowed, structurally orientated, and median/mean combination filters (Figure 3.11, right side). Small-scale fault identification is limited owing to heavy noise contamination, and noise reduction was paramount. Our filters began in a small window and were followed by progressively larger window filters. As in case study no. 1, we then used crosscorrelation-based spectral decomposition (Gao, 2013). Based on the visual inspection, we chose the 67 and 40 Hz volumes for our analysis. We also used the full-stack modified eigenstructure similarity (Garsztenkorn and Marfurt, 1999) for quality control. On each peak frequency volume, we computed a Sobel filter-based similarity (Al-Dossary and Al-Garni, 2013), which was followed by Pedersen et al. (2002)-style swarm intelligence and fault enhancement (Dorn et al., 2012). When calculating dip, we used a dip-scan method with a maximum of 60° and an increment of 2° (Marfurt, 2006). We then volumetrically summed these two volumes. The size of the original seismic data volume is approximately 25 GB, and the total size of all intermediate products, parameter tests, software projects, duplicated data, and SEGY exports was 2.6 TB (63 GB of final products). The total time required for computation was approximately 29 h, and required intermittent human interaction (to initiate a process).

Discussion and Results

The data set used in case study no. 2 is both contaminated by noise and heavily affected by poor acquisition coverage. This data set is of a lower fold and has an overall lower S/N than does case study no. 1. Nonetheless, spectral similarity greatly outperforms full-stack coherence and provides a clear indication of the complex fault systems present in the data (Figure 3.12). Specifically, the rectangle from Figure 3.12 highlights a complex fault system whose existence is hinted at in the full-stack similarity, yet it is not fully resolved. Spectral similarity allows the interpreter to identify and interpret these systems more effectively.

Conclusions

Fault interpretation remains a time-consuming and tedious task that is punctuated by moments of complexity and difficulty. Edge-detection attributes are a critical tool in the interpreter's toolbox to assist with and increase efficiency of fault interpretation workflows. We have demonstrated that our new method of similarity enhancement, spectral similarity, greatly increases the vertical and horizontal response of discontinuities. Moreover, we believe that spectral similarity lends itself quite readily to computer-based fault extraction techniques, and we have shown the potential for a dramatic increase in productivity when using this technique as a basis for such extractions. These improvements are a direct result of the inclusion of spectral decomposition, swarm intelligence, and orientated filtering into our workflow, which comes at a cost of computation time and scratch storage space. We provide for the use of curvature, total energy, or similarity style attributes combined into one fault detection volume. This enables the interpreter to identify which attributes highlight faults (or other linear features) optimally in their data set. Our spectral similarity workflow reduces or eliminates many algorithmic anomalies present in similarity attributes by estimating a more realistic fault dip, reducing noise, and removing stair-step discontinuities.

Figures

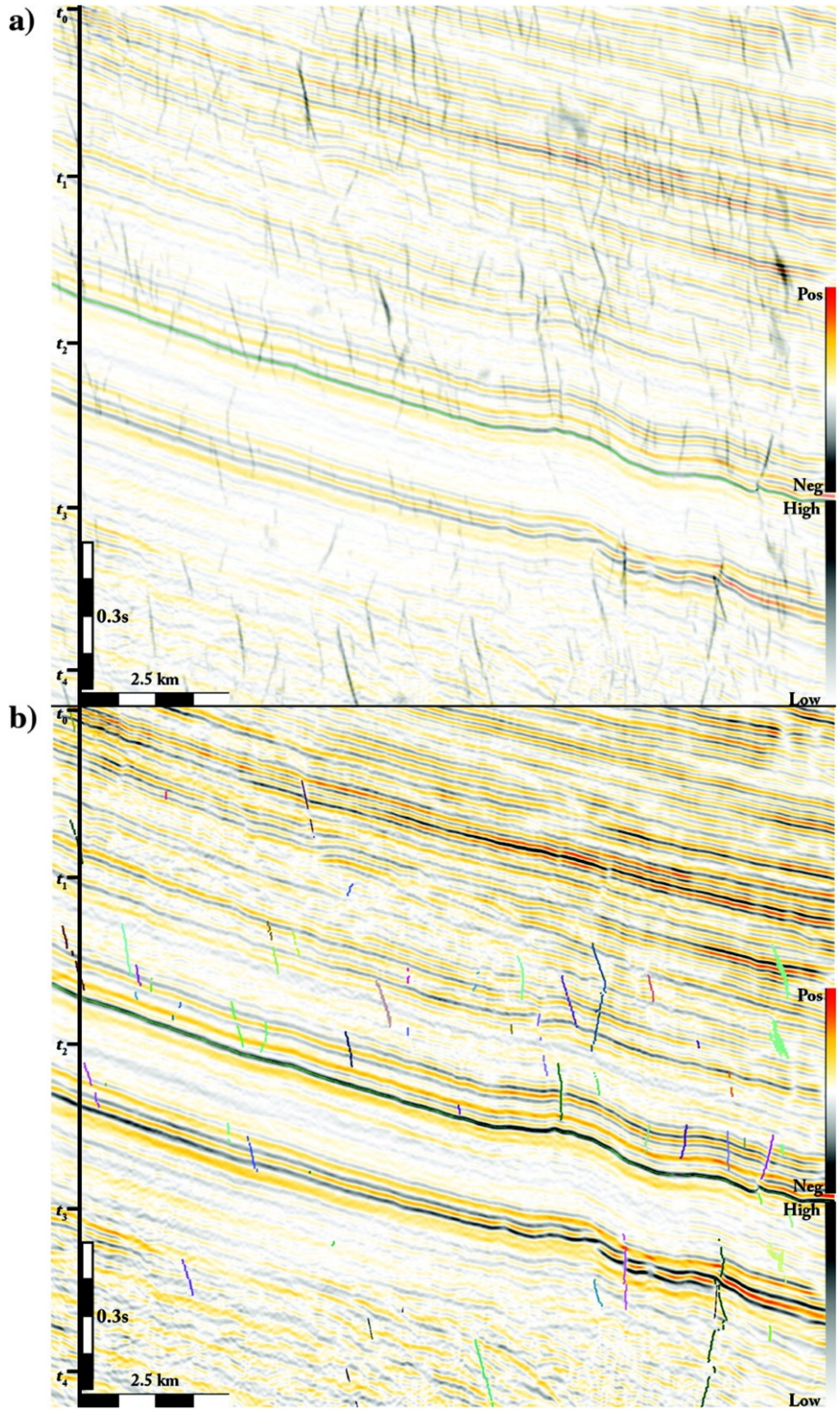


Figure 3.1: Spectral similarity vs. generated faults

Vertical section of the (a) spectral similarity co-rendered with seismic amplitude and (b) faults extracted using computer-based fault interpretation derived from the spectral similarity co-rendered with seismic amplitude.

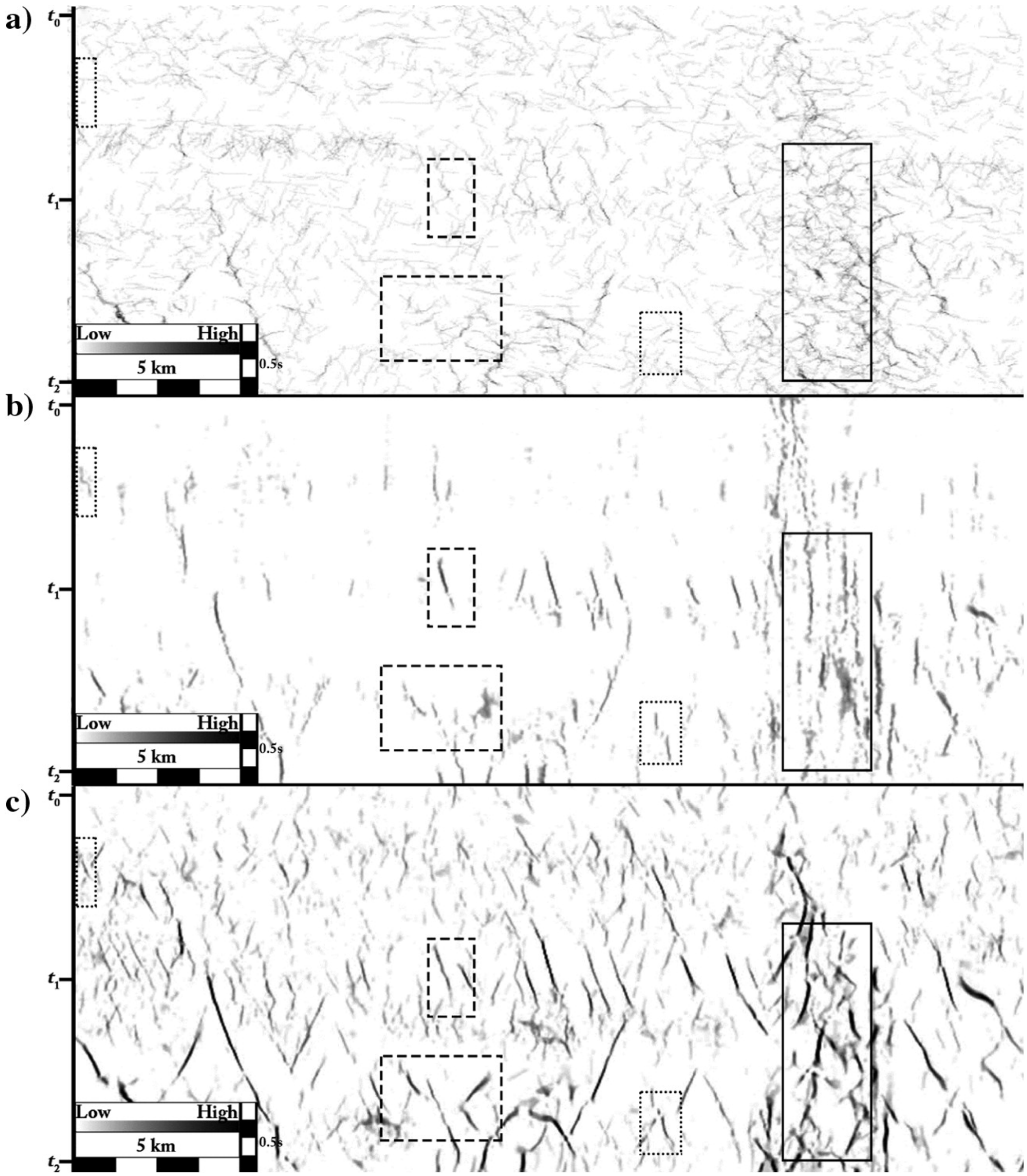


Figure 3.2: Visual comparison of various fault enhancement techniques
Composite vertical section image of the same crossline using various edge enhancement calculations. (a) Swarm intelligence method proposed by Pederson et al. (2002). (b) Strike- and dip-based enhancement proposed by Dorn et al. (2012). (c) Spectral similarity proposed in this paper. Three different classes of anomalies are highlighted based on the characteristics of the Pederson et al. and Dorn et al. style enhancements: (1) solid rectangles indicate areas of poorly imaged faults, (2) dotted rectangles indicate areas in which are moderately well imaged, and (3) dashed rectangles indicate well-imaged faults improved in the spectral similarity attribute.

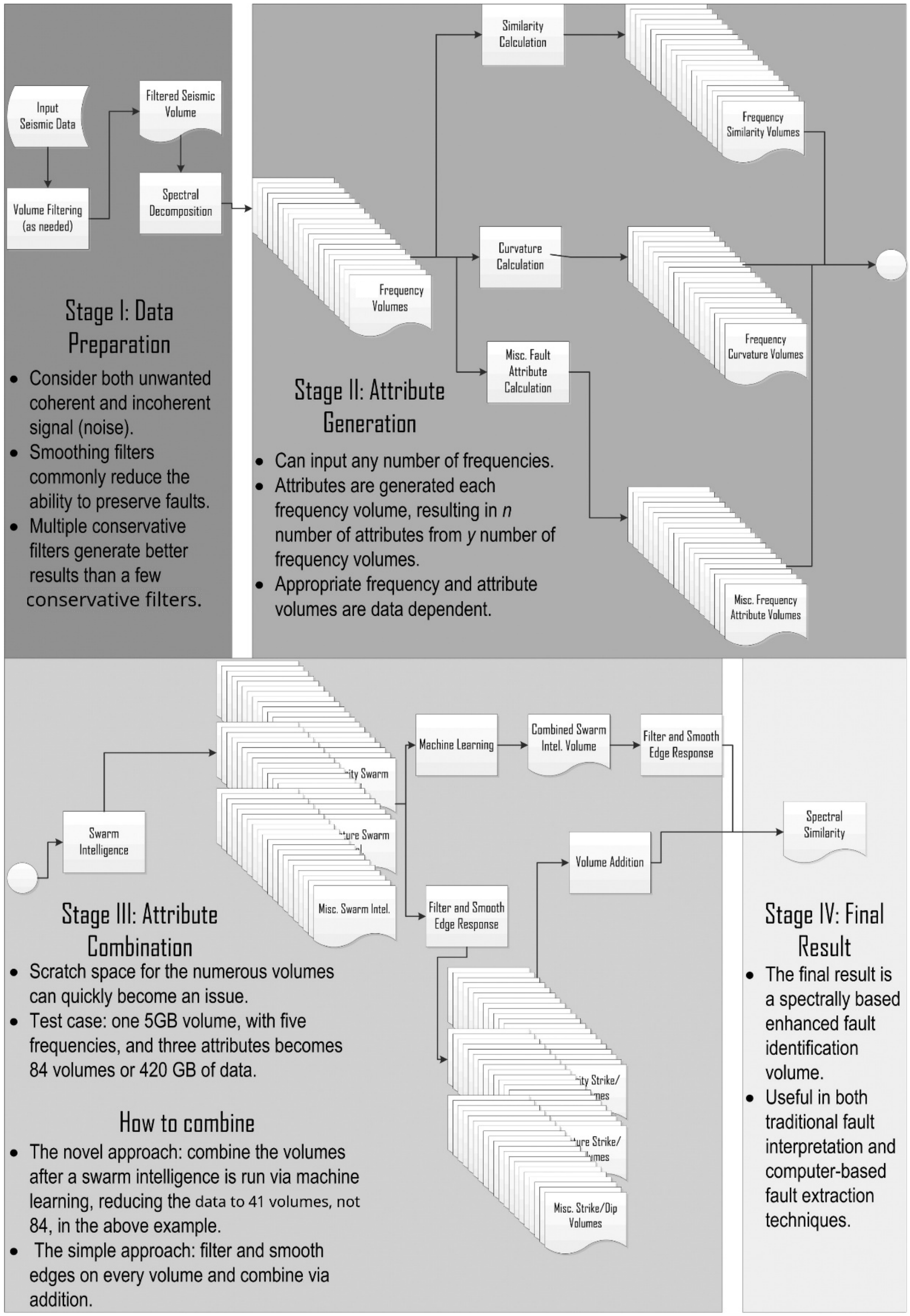


Figure 3.3: Spectral similarity workflow

The spectral similarity workflow and its four main stages of generation. The bifurcation in stage III allows for two different techniques to combine the results.

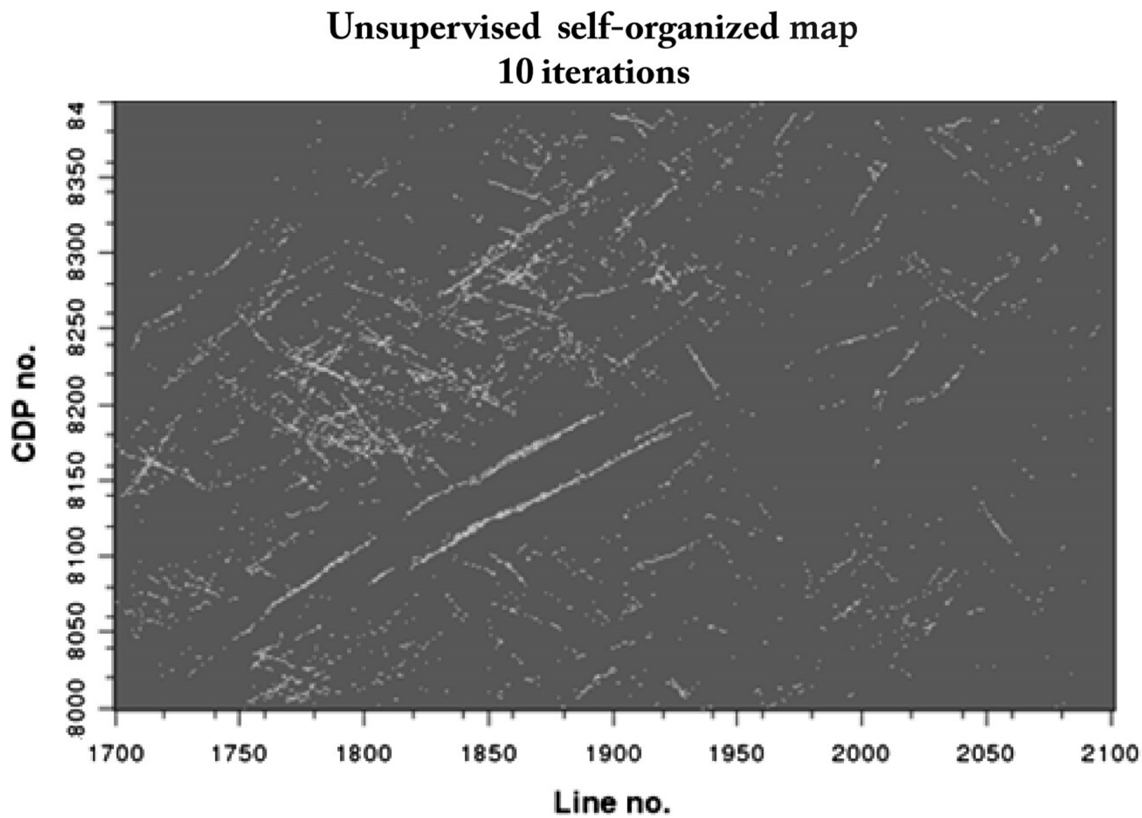


Figure 3.4: Using SOM to combine intermediate volumes

A time slice of a machine learning algorithm (self-organized maps) being used to combine three swarm-intelligence volumes into one prior to the filter and smoothing step. Each cluster represents contributions from different frequencies.

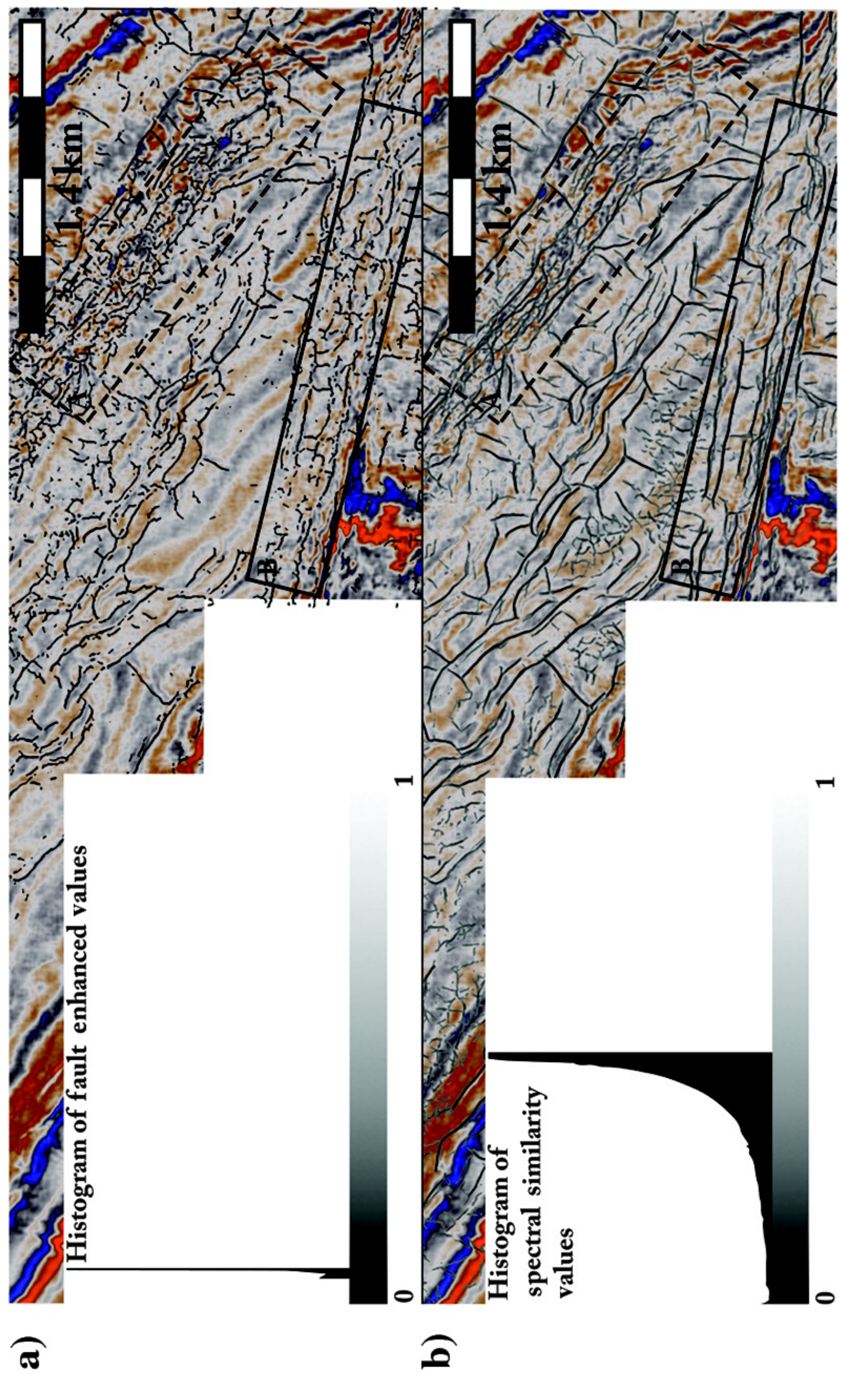


Figure 3.5: Visual comparison against leading commercial fault enhancement

Time slice through the seismic amplitude volume co-rendered with the (a) fault-enhanced similarity and (b) the spectral similarity that illustrates the data quality and lateral variation of seismic character in the data set. The rectangles highlight areas of interest, which include (A) a low signal-to-noise zone, (B) lateral changes to geology, (C) the response to stratigraphic thinning, and (D) a high signal-to-noise zone with large faults. A histogram for each similarity enhancement is shown highlighting the range of values of those volumes.

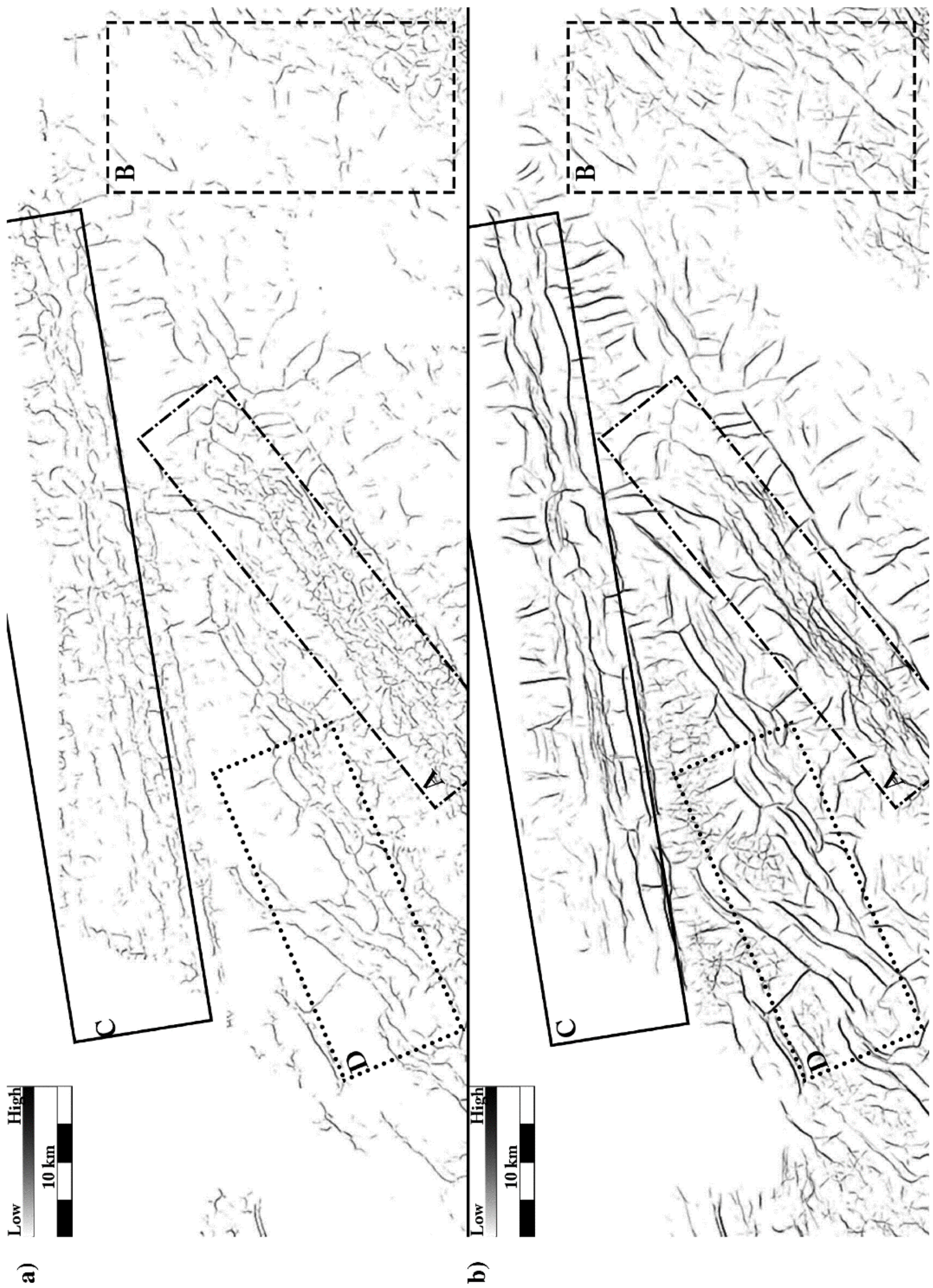


Figure 3.6: Visual comparison against commercial fault-enhanced volume

Time slice of the (a) fault-enhanced volume and (b) spectral similarity volume derived from the amplitude shown in Figure 5. In area A, the noise from a major fault zone makes any fault interpretation from the fault-enhanced volume difficult, whereas spectral similarity can easily interpret the major faults. The faults in the fault-enhanced volume in area B (which cuts into the overlying formation) have been filtered out. The faults in this same area in the spectral similarity are present and clear, owing to the multiple volumes that comprise the spectral similarity attribute. Similarly, areas C and D in the fault-enhanced volume lack the fault connectivity and clarity that is present in the spectral similarity.

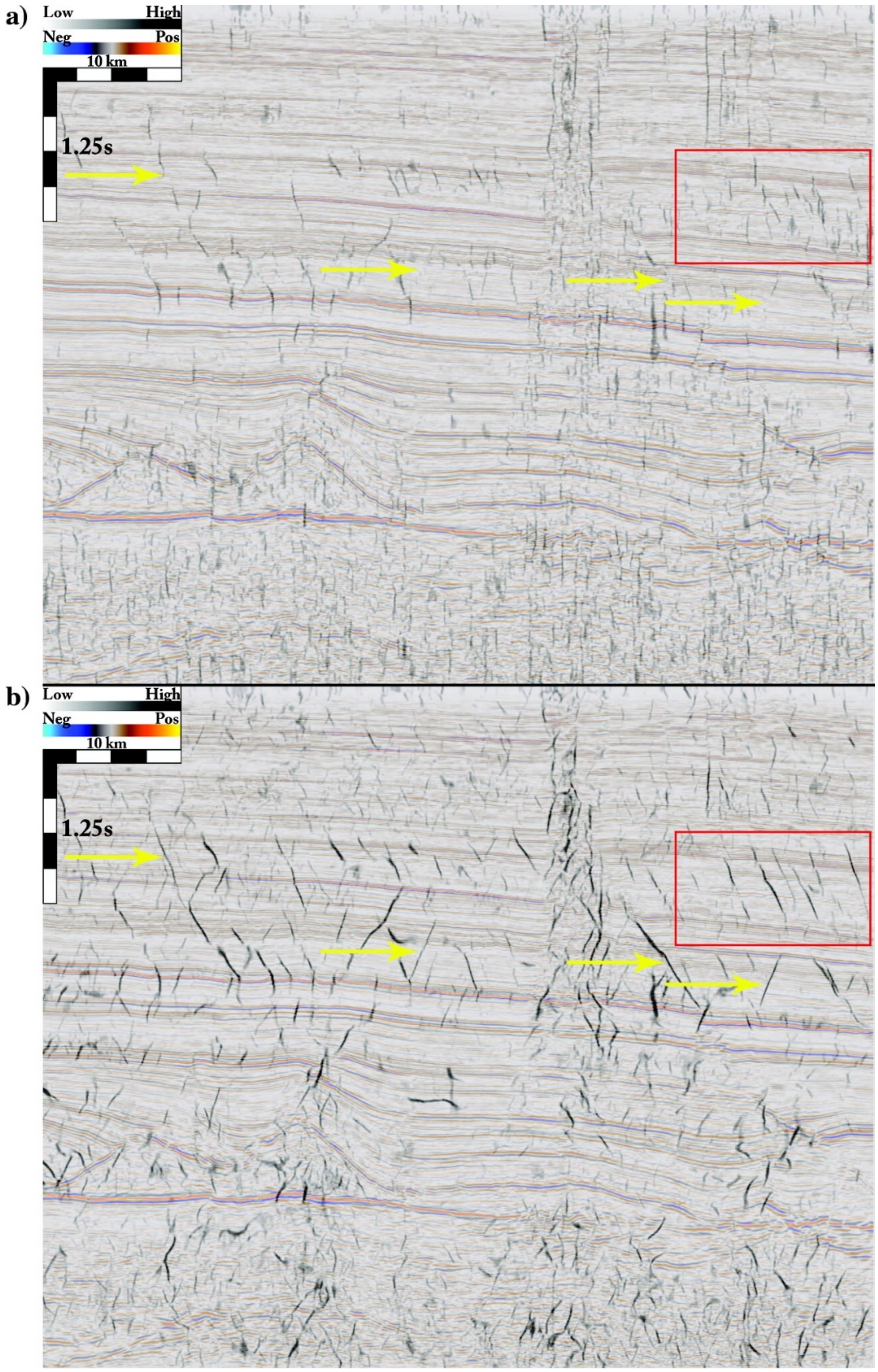


Figure 3.7: Visual comparison against commercial fault enhanced volume

Co-rendered vertical section comparing the results from the (a) fault-enhanced similarity enhancement and (b) spectral similarity. The red rectangle highlights an area where the spectral similarity shows more accurate fault dip, and the yellow arrows indicate areas where the spectral similarity has increased the connectivity of the fault response.

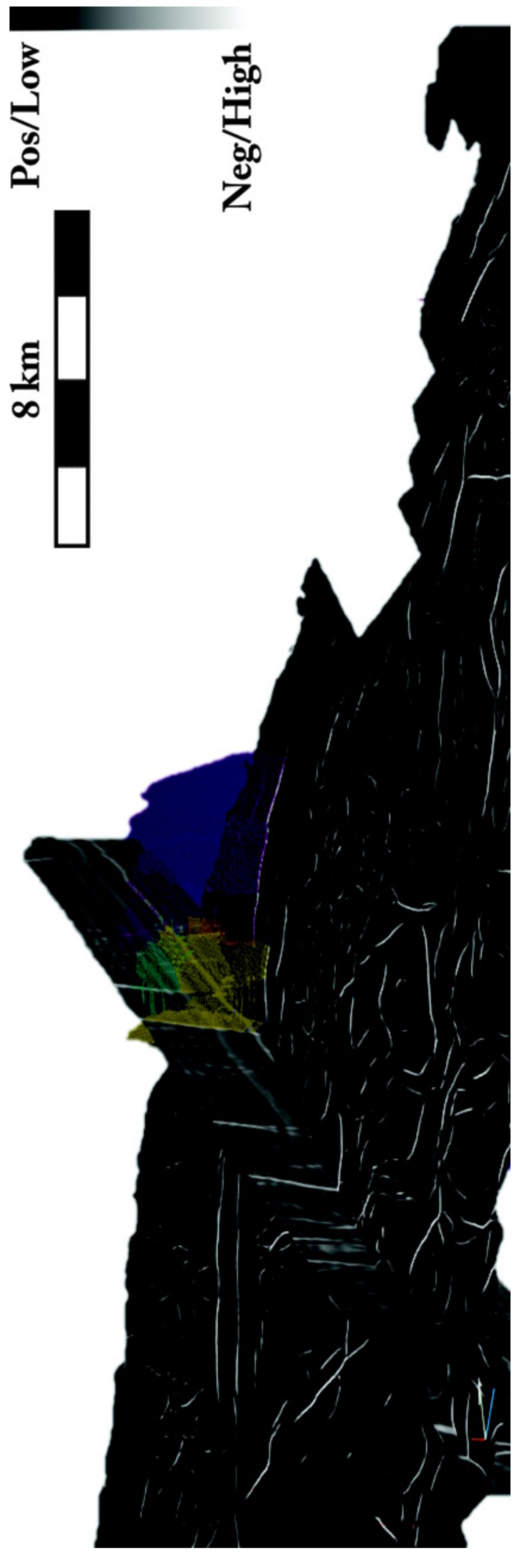


Figure 3.8: Example results from computer-based fault plane interpretation

Time slice from the spectral similarity rendered with a crossline of seismic amplitude illustrating results of semi-manual fault interpretation using commercial software. The yellow, blue, and purple points are interpreted as fault planes.

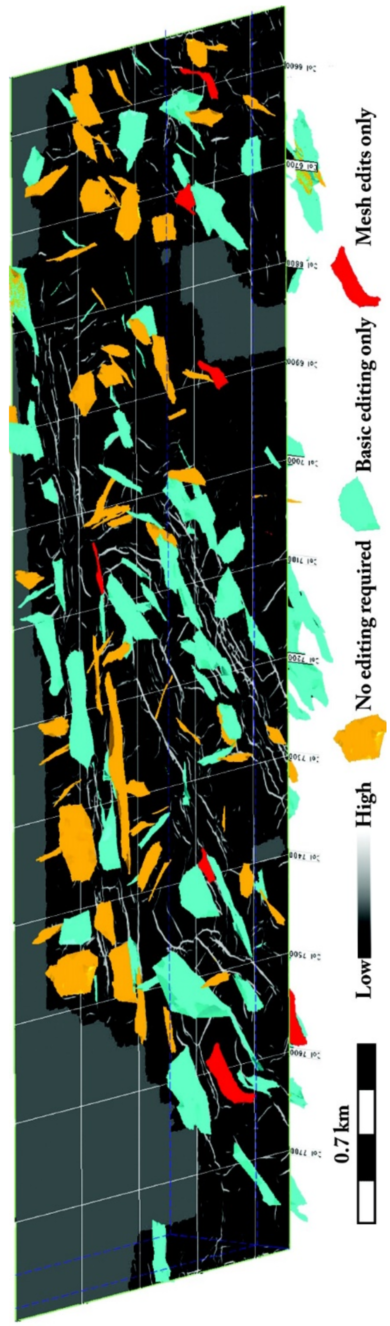


Figure 3.9: Results from computer-based fault interpretation (>10,000 points)
Computer-based fault interpretation using a minimum point population of 10,000 points per cluster rendered with the spectral similarity volume. The yellow faults require no edits, the blue faults require minor edits, and the red faults require interpolated mesh edits. The result was an increase in productivity of 6x–8x computer-based fault interpretations on other attribute volumes.

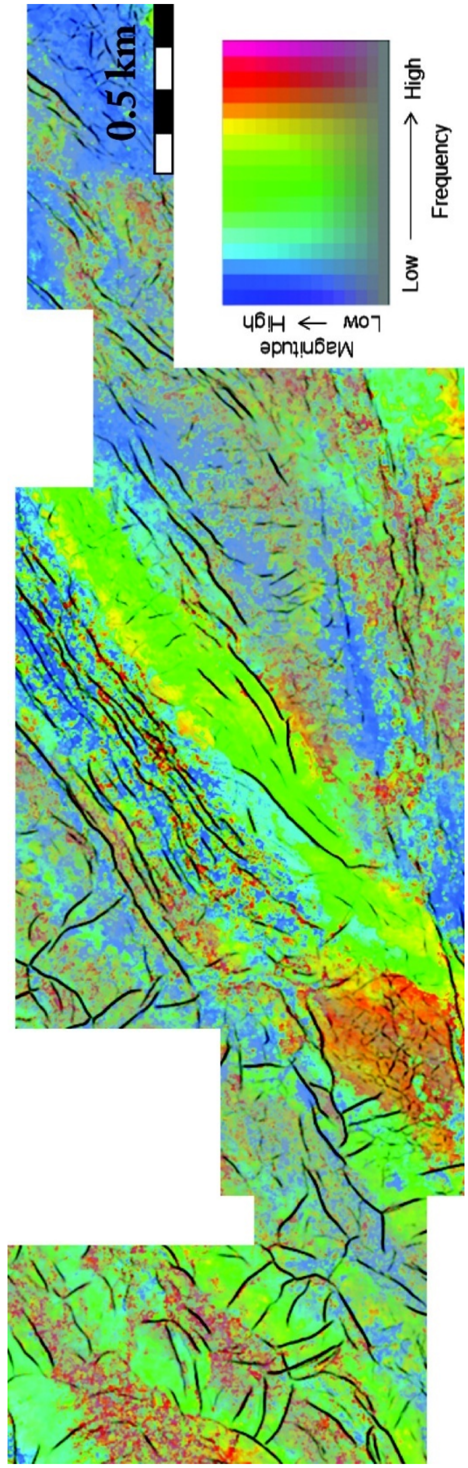


Figure 3.10: Co-rendered spectral decomposition and spectral similarity

Corendered time slice of peak frequency and peak magnitude from CWT spectral decomposition with the spectral similarity volume. Peak frequency/magnitude provides an indication of lateral stratigraphic variation, and the spectral similarity provides structural information.

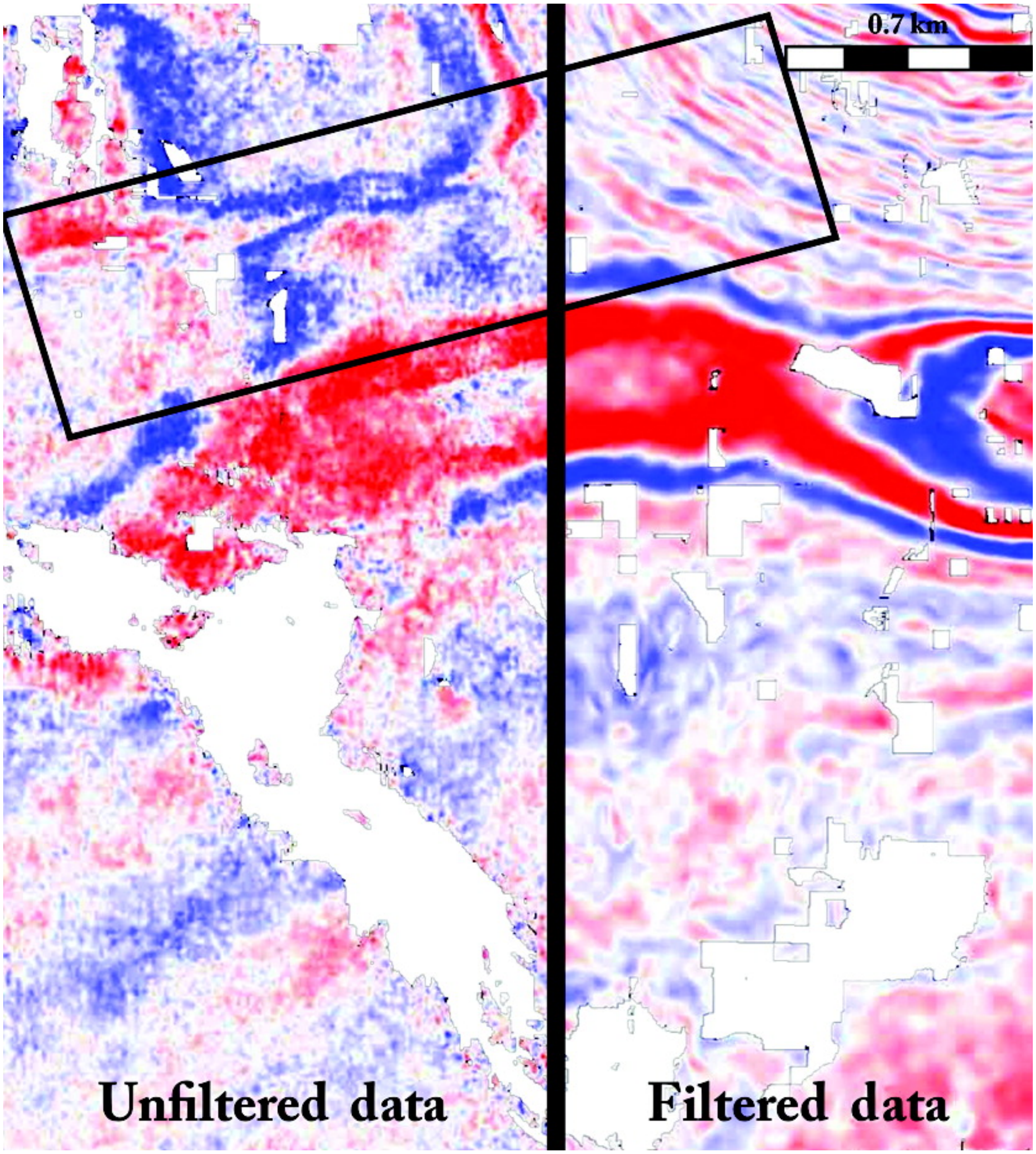


Figure 3.11: Comparison of before and after data conditioning

Time slice comparison of data prior to filtering and data after structure-orientated mean-/median-based filtering. The rectangle highlights a major fault zone in the data.

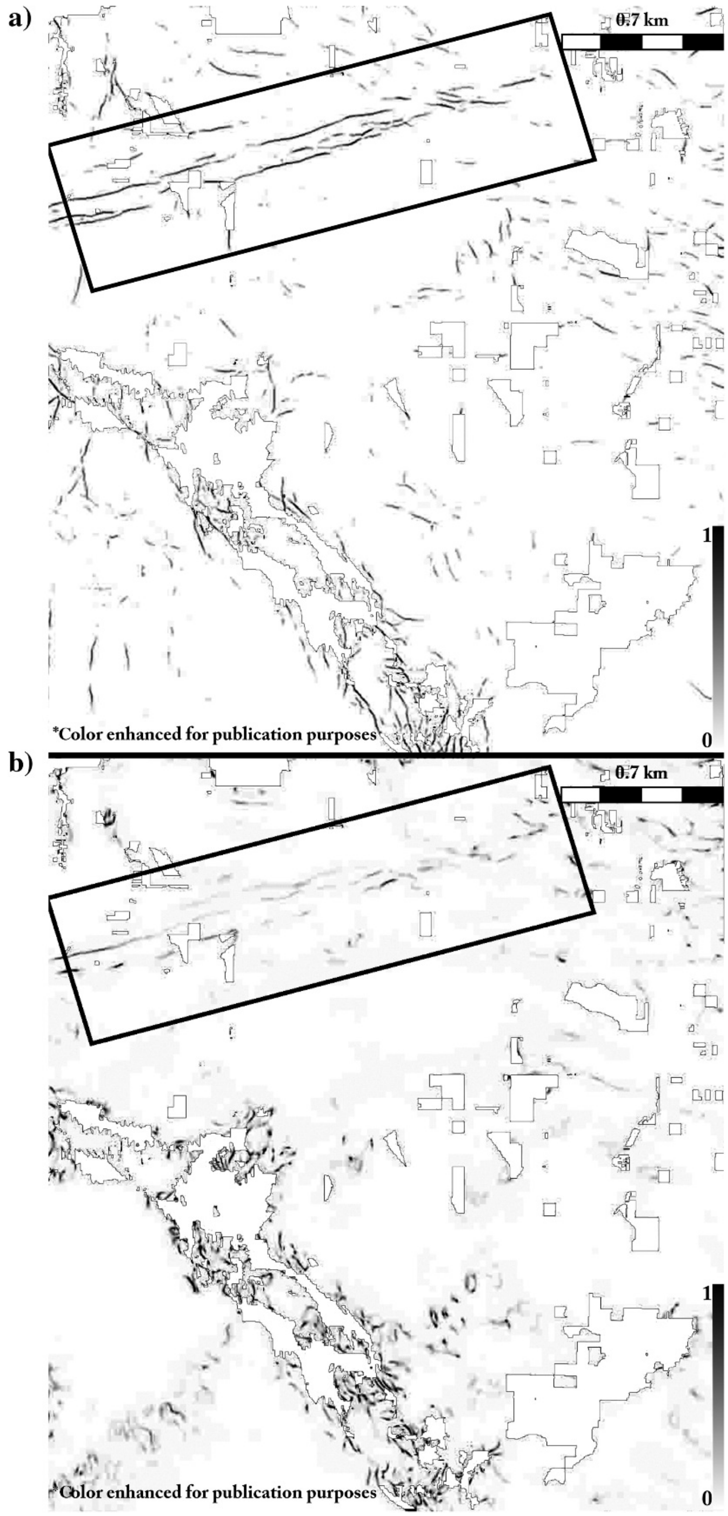


Figure 3.12: Comparison between spectral similarity and coherence

Time slice at the level of Figure 11 from (a) the spectral similarity volume and (b) a modified eigenstructure similarity. The fault zone highlighted by the rectangle is poorly resolved on the eigenstructure similarity, but it resolves into a trend of parallel faults on the spectral similarity.

References

Al-Dossary, S., and K. Al-Garni, 2013, Fault detection and characterization using a 3D multidirectional Sobel filter: Presented at the Saudi Arabia Section Technical Symposium and Exhibition, SPE, SPE-168061-MS.

Aqrawi, A., and T. Boe, 2011, Improved fault segmentation using a dip guided and modified 3D Sobel filter: 81st Annual International Meeting, SEG, Expanded Abstracts, 999–1003.

Bahorich, M. S., and S. L. Farmer, 1995, 3-D seismic discontinuity for faults and stratigraphic features: The coherence cube: 65th Annual International Meeting, SEG, Expanded Abstracts, 93–96, Crossref.

Basir, H., A. Javaherian, and M. Yaraki, 2013, Multi-attribute ant-tracking and neural network for fault detection: A case study of an Iranian oilfield: Journal of Geophysics and Engineering, 10, 015009, Crossref.

Dorn, G., B. Kadlec, and M. Patty, 2012, Imaging faults in 3D seismic volumes: 82nd Annual International Meeting, SEG, Expanded Abstracts, Crossref.

Gao, D., 2013, Wavelet spectral probe for seismic structure interpretation and fracture characterization: A workflow with case studies: Geophysics, 78, no. 5, O57–O67, Crossref.

Garsztenkorn, A., and K. J. Marfurt, 1999, Eigenstructure-based coherence computations as an aid to 3-D structural and stratigraphic mapping: Geophysics, 64, 1468–1479, Crossref.

Marfurt, K. J., 2006, Robust estimates of reflector dip and azimuth: Geophysics, 71, no. 4, P29–P40, Crossref.

Marfurt, K. J., R. Kirlin, S. Farmer, and M. Bahorich, 1998, 3-D seismic attributes using a semblance-based coherency algorithm: Geophysics, 63, 1150–1165, Crossref.

Partyka, Greg, James Gridley, and John Lopez. 1999. "Interpretational Applications of Spectral Decomposition in Reservoir Characterization." *The Leading Edge*, 1999. https://doi.org/10.1190/1.1438295.

Pedersen, S. I., T. Randen, L. Sønneland, and O. Steen, 2002, Automatic 3D fault interpretation by artificial ants: 72nd Annual International Meeting, SEG, Expanded Abstracts, 512–515.

Randen, T., S. Pedersen, and L. Sønneland, 2001, Automatic extraction of fault surfaces from three-dimensional seismic data: 71st Annual International Meeting, SEG, Expanded Abstracts, 551–554.

Chapter 4: Efficiency Gains in Inversion-based Interpretation

I have applied a Kohonen self-organized mapping algorithm (SOM) to allow for a rock physics based interpretation by non-specialists through the input of seismic attributes derived from amplitude versus offset (AVO) inversion. Specifically, the utilization of acoustic impedance (AI) and gradient impedance (GI) volumes, calculated from a colored inversion, allows any geoscientist to easily identify areas of interest that are consistent with a traditional rock physics analysis. This can be accomplished in a fraction of the time then traditional workflows. Moreover, this proposed initial screening is accomplished by personnel who are not trained in rock physics. Following the identification of these seismically anomalous regions, the engagement of a rock physics specialist can then be more efficiently employed in order to discern the subtle geophysical meaning of these SOM based anomalies. This minimizes the amount of time a specialist is required and maximizes the engagement of the general interpreter.

Introduction

Advanced geophysical analysis, a discipline consisting of quantitative seismic interpretation (QI), seismic attribute analysis, and associated workflows, is often a required step in the evaluation of a prospect in the oil and gas industry. In numerous basins, it is a virtual requirement to screen a prospect from a QI perspective prior to the risking and drilling of a well. The largest drawbacks of these methods are directly associated with the cost, both in monetary terms and in time, of the specialists that are required to play a heavy role in the entire evaluation process. From the initial screening of leads to the evaluation of a prospect prior to drilling, these QI specialists are in short supply, or non existent in some companies. A sometimes painfully obvious inefficiency exists that can increase the time required to evaluate a prospect, increase the cost with an idle geoscience team, add to the number of required consultants, and cause poor quality work.

By employing a computer-based classification algorithm from a QI perspective, it is possible to classify a seismic volume without direct human interaction. The resultant classes from such a method (often referred to as neurons) will be composed of groups of data points that either represent different parts of the background seismic character across the volume (i.e. the common background geology, Figure 4.1), or anomalous regions in the dataset (Figure 4.2). Since most targets in exploration geophysics are appropriately described as rare occurrences, these anomalous regions are of significance.

Method

Self-organized maps (SOMs) were first described by Kohonen (1989). Derived from research in artificial neural networks, a SOM is trained using unsupervised learning that is used to reduce the dimensionality of the input space training samples (referred to as a map). Although the SOM is a type of neural network, it is important to note that the architecture of the SOM is radically different to a feed-forward neural networks that are more commonly envisioned when invoking the more general term of neural network. Fundamentally, the SOM is designed to preserve the topology of the input space by implementing a training algorithm known as competitive learning. In this scheme, the nodes compete for the right to classify a given response in the input space during the SOM training. It turns out that as the number of classes (nodes or neurons) decreases; the results approximate K-means clustering; however, as the number of classes increase, the results are topologically related to the input space

The resultant set from a SOM-based classification is critically dependent on the input data. It is common to use many seismic attributes in the hope to derive seismic facies. Commonly, when a SOM is employed (even with a desire to link the rock physics), there is a tendency to overpopulate to algorithm with numerous inversion products (Zhao et al., 2015). This limits the value of the output and masks the underlying rock physics, which are critically important. However, in this application of computer-based classification, it is critical that the link between the rock physics and the resultant set remains strong. This can be achieved by limiting the number of input data sets to only physically meaningful and mathematically uncorrelated seismic attributes. I have chosen to use only the acoustic impedance and gradient impedance volumes from a band-limited colored inversion, as described by Connolly (1999). Figures 4.3 and 4.4 show the AI and GI data, respectfully, for the reference inline shown in Figure 4.1.

Geologic Background

The dataset that is being used is offshore Australia in a known hydrocarbon producing province. Structurally, this region is dominated by regional extensional tectonic events, which cause pervasive normal faulting at the intervals of interest. Wells were neither directly used in the classification, nor were they used to influence the identification of the classes of interest from the resultant classification. The data quality is fair to good depending on the depth and structural complexity. There are several known high porosity sands in the basin; some are known hydrocarbon producing (oil) and some are known to be brine saturated.

A rock physics template has been completed for this area previous to this study, and it will influence the geophysical interpretation of the results. However, this rock physics analysis does not influence, in any way, the initial screening, which was accomplished with little knowledge of the basin or of the rock physics for this region.

Results and Conclusions

From the input attribute to the classification (AI and GI), one would expect that the noisy nature of the GI volume, in particular, would impact the ability to classify the various stratigraphic units correctly. Additionally, there is expected separation in AI-GI space for oil and brine in highly porous sands in this basin, it may prove difficult for that the SOM to distinguish between these two cases. This is owing to the fact that the intent of the SOM is to classify the entire seismic character across the entire volume, and the number of classes are limited to a specified number. I will show three cases: a small number of classes (16), a moderate number of classes (64), and a large number of classes (256).

If one begins with a simple case of four classes, more events that are actually different will be grouped together owing to too few classes being able to represent the data adequately. As a corollary, as the number of classes approaches a somewhat large number (e.g. 4,096 with two input attributes), many of the classes will have only one (and sometimes zero) voxels representing. One could intuitively expect that a practical workflow would be to begin with a small number of classes and progress to some optimal number in order to distinguish and further focus one’s area of interest. Figure

4.5 shows an example using only 16 classes, which can serve as a case for initial screening.

As shown in Figure 4.6, by increasing the number of classes, one is able to remove the majority of the events on the right-hand side of the image in Figure 4.5 as a different class. It turns out that these will become grouped into one of the "background" response classes in this class topology.

By increasing the SOM classes to 256, the ability to differentiate becomes somewhat more difficult. This is owing to the algorithm producing too many divisions that result in needing to use numerous classes to highlight a layer of interest. Because we don't know the layer of interest in advance, this is quite difficult and can easily result in incorrect interpretations. In pristine data with a very clean gradient, this level of distinction may prove useful; however, in this case, I would recommend against its use. The results of the 256 class topology are shown in Figure 4.7.

The next step in the analysis involves understanding the rock physics for this basin and analyzing available well data. As stated previously, from the rock physics analysis, one would expect good separation between oil and brine in the expected sands in this area. Further information from a well on the shown reference line indicates that the lower event at about t0+1s and between x0 and x0+5km is a producing oil-rich highly porous sand. The upper event (previously identified as just above the unconformity) is a brine filled sand with no economic potential. However, even though it has a similar AVO response, one can easily identify that there is little change for a trapping mechanism in this region. Finally, the small anomalies to the left and right of the main producing zone are brine filled sands with no economic potential.

When conducting an attribute analysis, it is highly beneficial to understand the basic physics and mathematical dependence on the attributes utilized. A self-organizing map approach is no different in this aspect. Although uncommon, using only two attributes as an input can be highly beneficial and can reduce the time required for prospect analysis. This is especially true if the analysis requires the knowledge of an experienced specialist, who can be considered an uncommon skill-set in many environments, especially in smaller oil and gas companies.

During the parameterization process, it is critically important to choose the number of classes appropriately. Fortunately, it is a simple matter of starting with a small topology and progressing to a larger one. As an alternative to larger topologies, one can elect to invoke a probability style filter on the classification, which is related to the standard deviation of the grouping in the input space.

Although I have shown Class III AVO anomalies, it can be shown that these methods will also assist in the identification of any AVO class, including the difficult to identify Class II-P. However, as one would expect, it is suggested that in these situations the SOM is accompanied by a rock physics analysis to include analyzing the gathers directly.

While not a replacement for foundational knowledge of rock physics or geologic understanding, by using a computer-based classification such as a SOM, it is possible for less specialized geoscientists to mimic the results that a traditional rock physics specialist could achieve. The primary importance of this is to both engage the general interpreter in the rock physics analysis and allow specialists to apply their trade in a more time efficient manner.

Since general interpreters typically have more in-depth basin knowledge than the specialist, they will tend to view the SOM results with a geological lens rather than a geophysical one. This increase in perspectives can only benefit the rock physics analysis that is necessary following the initial screening as prescribed above. As a final point, although I have correctly identified the known producing sand with no basin knowledge or prior rock physics knowledge, it is clear that this workflow cannot be the end of the QI analysis. An analysis similar to the workflow above should be the beginning of a more detailed study that is now localized in very specific areas of interest.

Figures

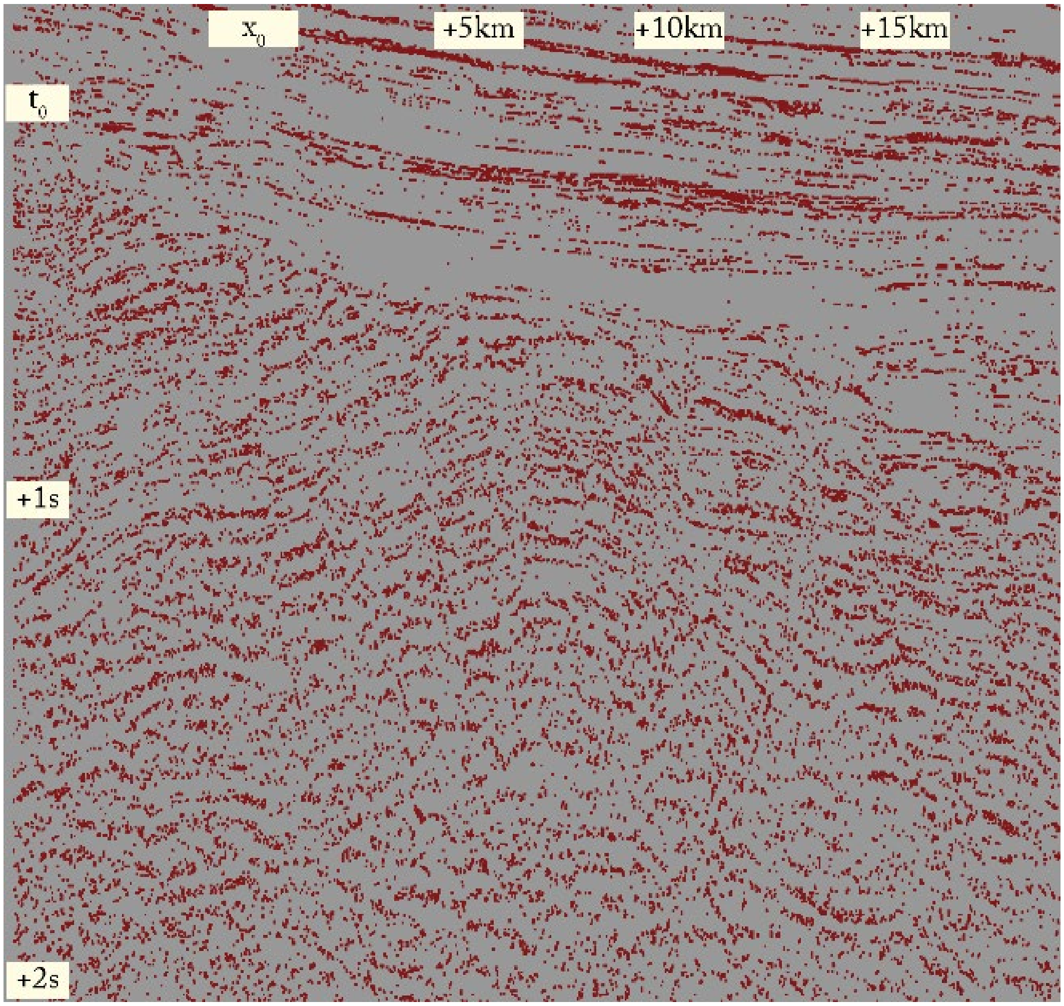


Figure 4.1: Example single class output from a SOM (background)

A reference inline section in the time domain that will be used throughout this study. This section shows an example of a single class from a SOM based classification. Since the input attributes to the classification were band-limited inversion products, it is expected that the classes will resemble the geometry of the seismic data. In this case, this class is near a zero crossing response with a near zero gradient. The pervasive nature of the response throughout the volume strongly suggests that this class represents part of the background response of the seismic data. In such cases, it is easy to identify this and exclude these classes from further analysis without any actual knowledge of the seismic character described above.

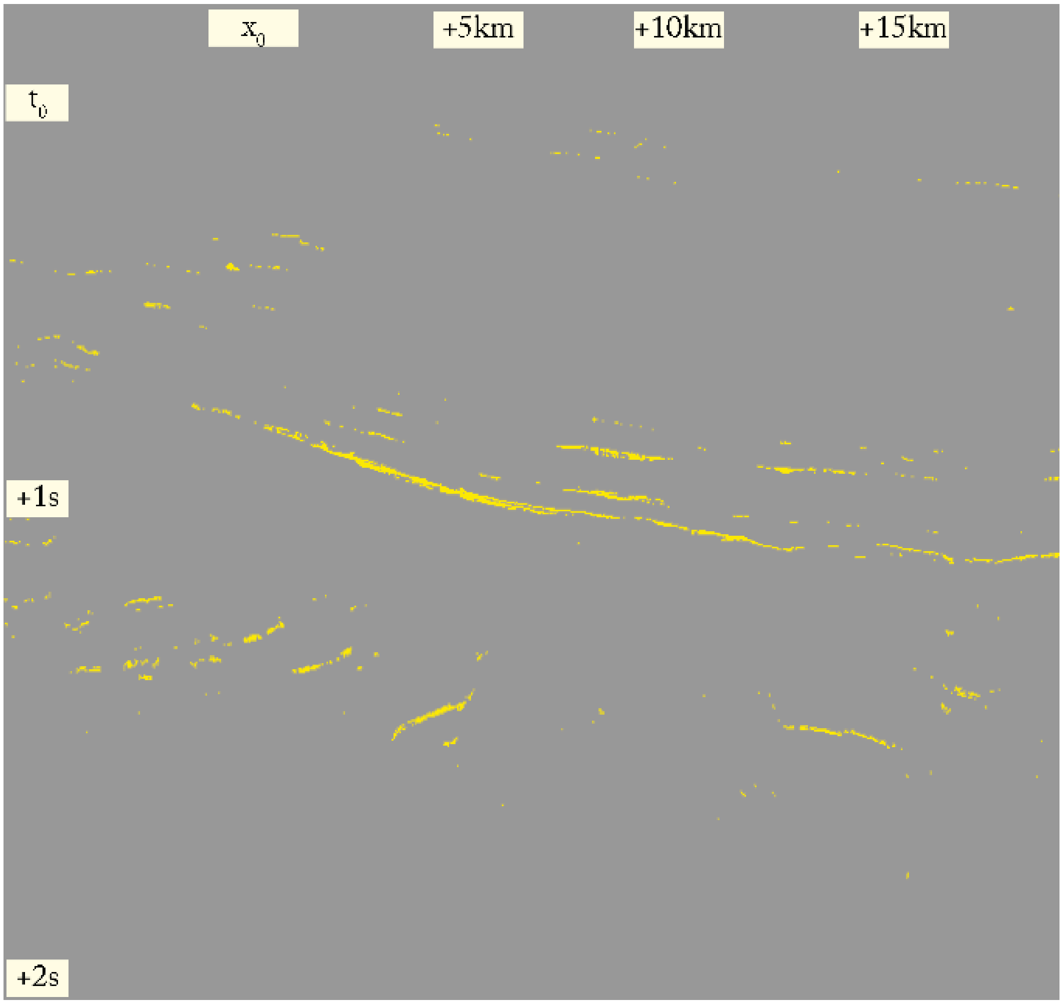


Figure 4.2: Example single class output from a SOM (anomalies)

This vertical section (reference inline) shows an example of a single class from a SOM based classification. Unlike Figure 1, where the class clearly represented the general background data, this class is highly localized. One can infer from the localization that this class highlights an AI and GI response that is atypical for this inline and, by extension, this dataset. By taking this further than simple pattern recognition, a geologist familiar with this basin would immediately recognize that the near continuous reflector at about +1 seconds is a well-known sand on the top of a regional unconformity. A simple geophysical analysis of this class will quickly reveal that it is a strong negative AI combined with a strong negative GI, representing a Class III AVO response.

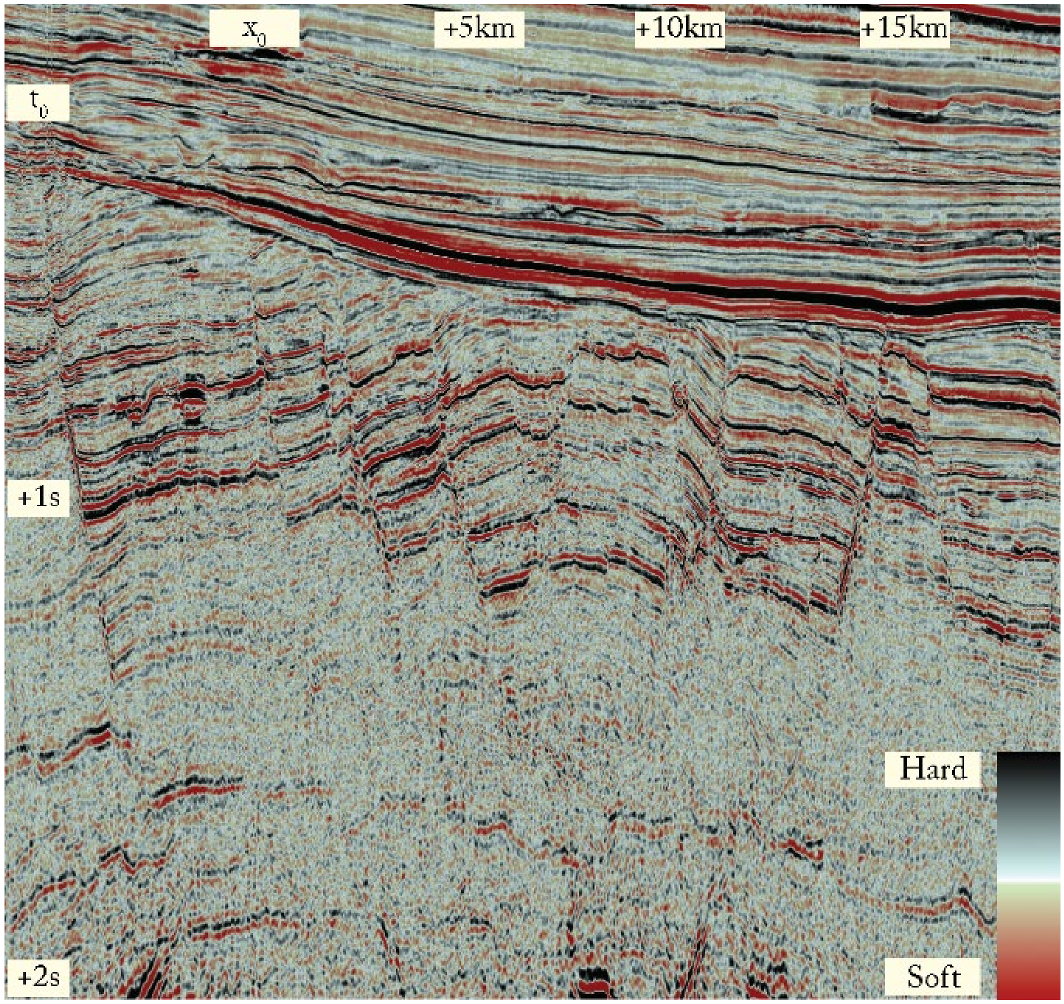


Figure 4.3: Acoustic Impedance for Reference Line

The acoustic impedance (AI) attribute derived from a colored inversion of the seismic amplitude data is shown in this reference inline. Immediately, one can distinguish the large soft response above the unconformity that extends across the line, located just below t_0. The large package of faults at t_0+1s, is an extensional fault system. The regional geologic setting would place any intervals of interest at this level. The seismic quality can be described as good above the unconformity and fair below it. Moderate levels of noise are present upon close inspection, especially when the structure becomes complex.

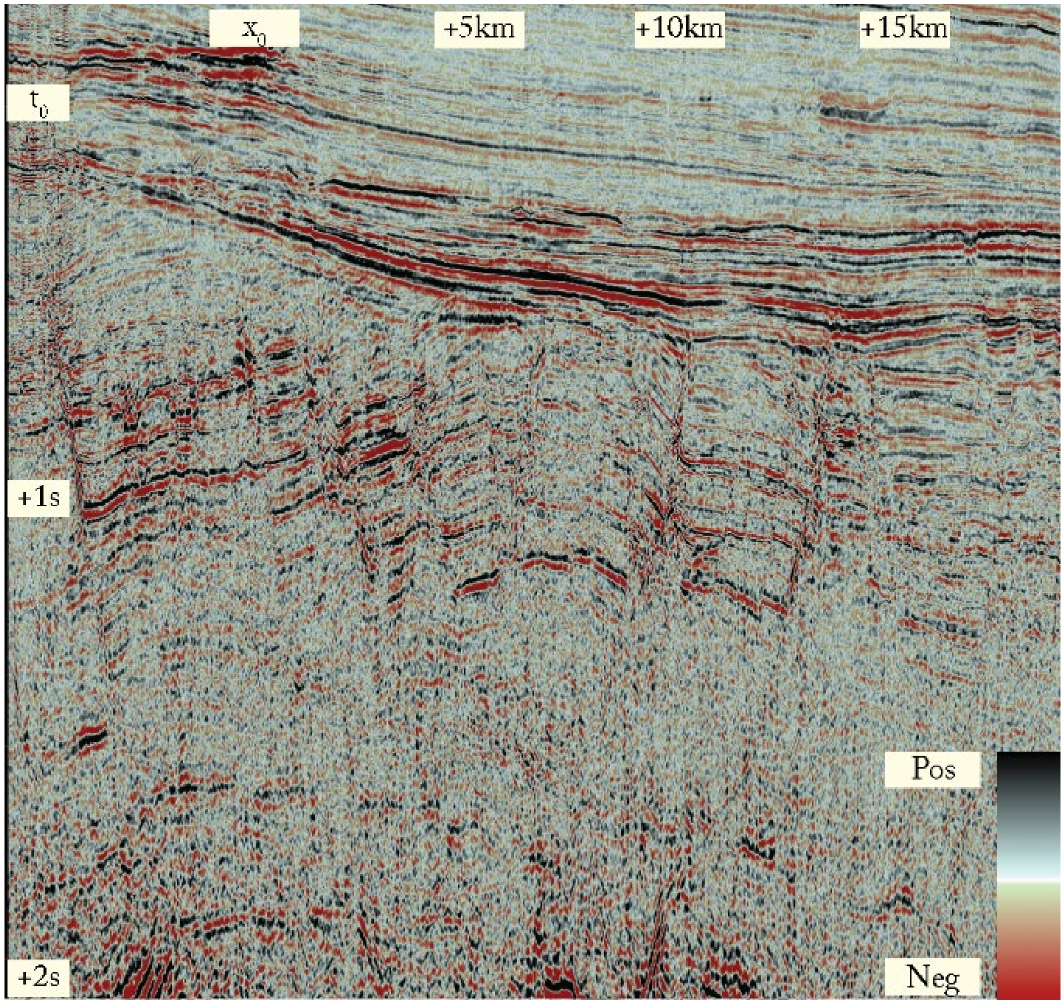


Figure 4.4: Gradient Impedance for Reference Line

This vertical section (reference inline) is the gradient impedance derived from a colored inversion. Black is a positive gradient, red is negative gradient. Below the unconformity at t_0, the noise in the gradient becomes quite heavy. Any analysis based on this data will be influenced by this noise.

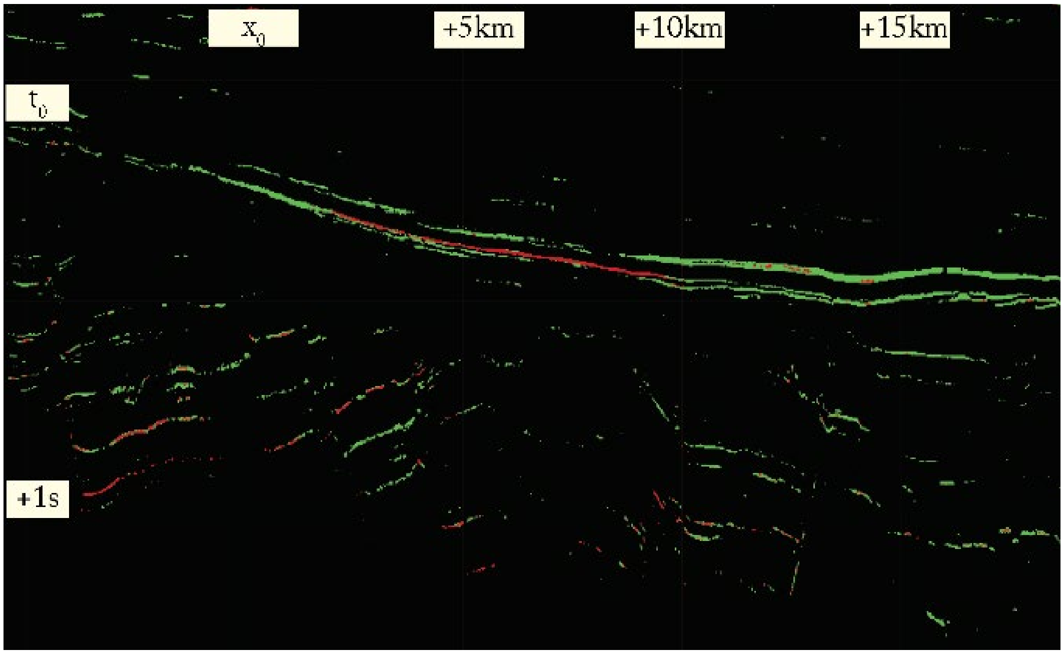


Figure 4.5: Results from a 16 class SOM

By using a small number of classes (16) as an initial screening tool it quickly becomes obvious which areas of the data are most anomalous, and, therefore, of most interest. The colors represent class grouping only.

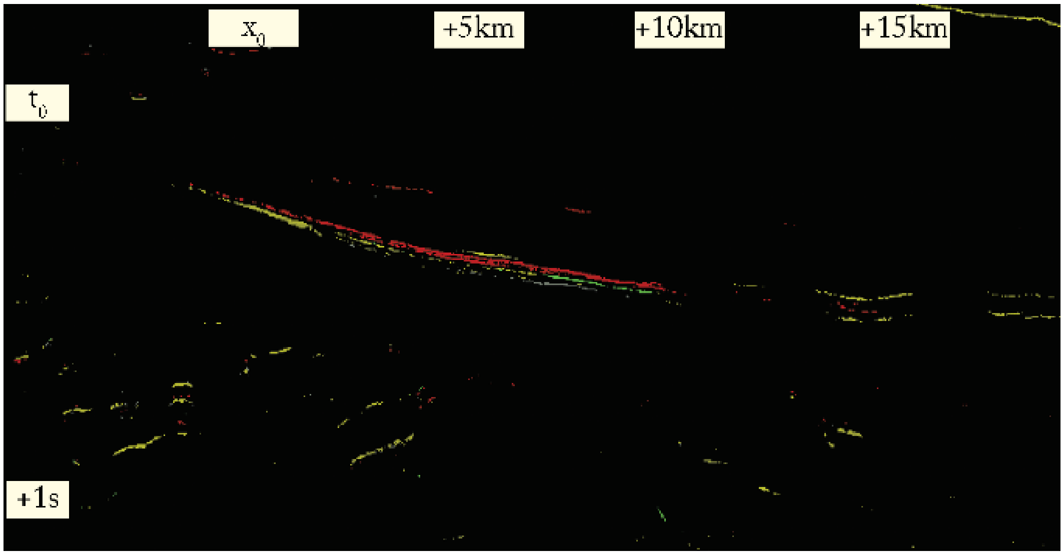


Figure 4.6: Results from a 64 class SOM

By increasing the number of classes to 64, we can further isolate portions of the unconformity and the sands below. Notice that the top-left portion of the unconformity is the same class as the majority of the events below.

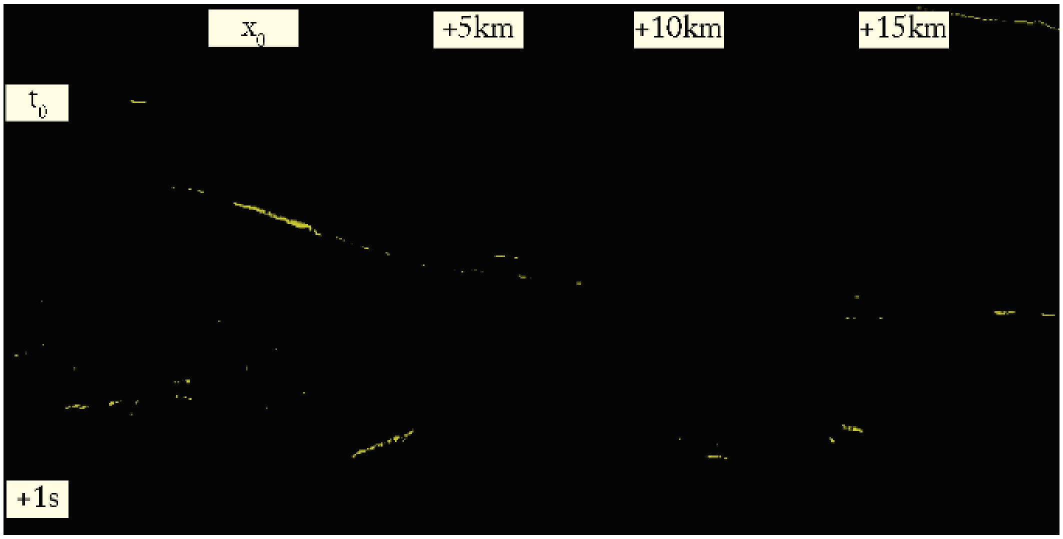


Figure 4.7: Results from a 256 class SOM

By using a large number of classes, I have identified five classes (all colored similarly for illustration) that highlight the most anomalous soft AI events (likely sands). It is not possible to distinguish between the response of the unconformity dipping down from left to right and the lower sand dipping up from left to right. These two intervals appear to have very similar AVO character. At this point one would need to evoke a geologic understanding to differentiate these events (with the lower event as a potential reservoir).

References

Connolly, P.A., 1999, Elastic impedance: The Leading Edge, 18, 438-452, doi: 10.1190/1.1438307.

Kohonen, T., 1989, Self-organization and associative memory, 3rd Edition, Springer, New York.

Tao Zhao*, Sumit Verma, Jie Qi, and Kurt J. Marfurt (2015) Supervised and unsupervised learning: how machines can assist quantitative seismic interpretation. SEG Technical Program Expanded Abstracts 2015: pp. 1734-1738. doi: 10.1190/segam2015-5924540.1

Chapter 5: Conclusions

In this dissertation, I explored the use of seismic attributes and approaches to their use in real-world scenarios. Perhaps the use of seismic attributes was at its height in the 1980s and 1990s when most seismic attributes were being developed with great enthusiasm. However, as our algorithms become more sophisticated, the inputs to the result become obscured. To use these new tools effectively, we must understand both the history of seismic attributes, their historical use, and to what level they are effective. Then we can leverage machine learning approaches in such a way as to add obvious benefit, rather than claims driven by commercial interests.

In Chapter 2, I explored the history of seismic attribute classification and taxonomy. We began with a survey on every major seismic attribute taxonomy in existence, followed by an analysis of their historical use. I described conceptual domains, which are rooted in data analysis, to argue that a combined approach in each of the major domains will provide a foundation to facilitate communication across technical backgrounds and disciplines. I ended the section with three seismic attribute taxonomies, one for each identified domain, and showed how each relates to one another by cross-referencing them.

In Chapter 3, I reviewed a method of fault enhancement which I developed prior to the creation of more recent convolutional neural network algorithms. This was a novel and creative method of filtering and attribute combination that is only surpassed by a well trained CNN model. However, the method described does not vary significantly from one dataset to another, while we must train a CNN model for a specific structural domain. This technique has, since its original publication, catalyzed several related research projects, which have built upon my work by adding multi-spectral aberrancy and curvature to my multi-spectral coherence. A well-done multi-spectral coherence was developed by the University of Oklahoma, which removes my requirement of commercial software.

In Chapter 4, I investigate the use of SOMs, an unsupervised machine learning or clustering algorithm, to determine the potential efficiency gains by using traditional QI products in a SOM. Specifically, I investigated the question “Can a general interpreter leverage SOM and QI products to identify areas of interest without a QI background?” I showed that this is both possible and effective. I also illustrate how a SOM behaves at its most basic level. This has some additional educational value as more and more geoscientists use SOMs and other clustering methods to interpret their data.

As geoscientists use machine learning at an increasing rate, there is a potential for both great efficiency gains and incredible misuse of that technology. By understanding the foundations of seismic attribute analysis and how this field relates to quantitative seismic interpretation, geoscientists can have both a higher level of understanding and greater expectations of those products when they encounter them.