Nigerian Journal of Applied Physics (NJAP)
ISSN Print: 3115-5871
ISSN Online: 3115-588X
DOI: https://doi.org/10.62292/njap-v2i3-2026-14
Volume 2(3), September 2026

# Application Of Spectral Decomposition For Structural And Stratigraphy Identification In Central Niger Delta

***[1]Ngeri Aminayanasa Paddy, [2]Dieokuma Tamunosiki and [1]Amonieah Jiriwari**

[1]Department of Physics, Rivers State University, Port Harcourt, Rivers State, Nigeria.
[2]Depatyment of Physics, Federal University, Otuoke, Bayelsa State, Nigeria.

[*]Corresponding author's email: ngeri.aminayanasa01@ust.edu.ng

**ABSTRACT**

This comprehensive study evaluates the efficacy of Spectral Decomposition in refining seismic data interpretation, particularly in identifying subtle geological features such as faults, channels, and point bars. Utilizing Petrel and OpendTect software packages, we analyzed 3D seismic datasets from both land and marine environments, employing a multi-stage approach that involved conventional seismic interpretation methods and advanced Spectral Decomposition techniques. Our results demonstrate that Spectral Decomposition significantly outperforms conventional methods in delineating faults and channels, revealing structural and stratigraphic traps that are often obscured in traditional time-slice analyses. By enhancing the visibility of sub-seismic faults and complex geological features, Spectral Decomposition enables geologists and geophysicists to improve well placement accuracy, target prospective zones more effectively, and optimize exploration and production strategies. This study highlights the potential of Spectral Decomposition to revolutionize seismic data interpretation and its applications in hydrocarbon exploration.

**Keywords**:
Spectral Decomposition,
Continuous Wavelet Transform,
Short-Time Fourier Transform,
Fault,
Channels,
Point bars.

## INTRODUCTION

The increasing demand for hydrocarbons has driven exploration into more complex and remote environments, such as deep waters and dense jungles. To meet this challenge, the industry is developing new geophysical techniques and refining existing ones to improve the accuracy of hydrocarbon reservoir mapping (Holdaway & Irving, 2017; Lai *et al.*, 2022; Ngeri *et al.*, 2024). The process involves several critical steps: seismic data acquisition, processing by geophysicists, interpretation by experts, and finally, drilling based on the interpreted data. Accurate interpretation is crucial, as errors can lead to drilling failures (Ngeri *et al.*, 2024).

Prior to drilling, advanced interpretation algorithms like Spectral Decomposition is essential for visualizing subtle geological structures, such as channels, sand bodies, and faults, that are often obscured in conventional seismic data (Yan *et al.*, 2017; Kobr, 2021; Ngeri *et al.*, 2024). These structures play a crucial role in identifying potential hydrocarbon prospects. However, conventional seismic data can make it challenging to detect these features, especially when analyzing time slices. Spectra Decomposition can significantly enhance the visibility of these structures, allowing for more accurate interpretation (Chopra & Marfurt, 2007; Ngeri *et al.*, 2024). By applying Spectra Decomposition to time slices, interpreters can better identify hidden geological features, such as river channels, which are often more apparent in time slices than in vertical sections.

Conventional seismic interpretation methods have limitations, which can become apparent during the drilling of production wells, potentially leading to costly issues such as drilling mud loss (Ambati *et al.*, 2021; Gabdullin, 2023; Ngeri *et al*., 2024). One major challenge is mapping sub-seismic faults, which can absorb drilling mud and cause well abandonment if not properly understood (Ashique and Samiranjan, 2010; Ngeri *et al*., 2015).

Various studies have demonstrated the effectiveness of spectral decomposition in reservoir characterization. For instance, Torrado *et al.* (2014) utilized spectral decomposition within a specific frequency range (46.3 - 55.9 Hz) to identify thin channels within broader channel belt complexes, enabling the prediction of sand distribution and preservation of abandonment channel facies. Similarly, Castagna *et al.* (2003) applied matching pursuit spectral decomposition to detect low-frequency shadows beneath hydrocarbon-bearing reservoirs. Other researchers, such as Peryton et al. (1998), have combined spectral decomposition with coherence attributes to interpret incised valleys hidden in seismic data. Additionally, Partyka *et al.* (1999) employed fixed-windowed spectral analysis to generate discrete-frequency energy cubes, which have proven useful in reservoir characterization.

Research by Mirza and Philips (2014) utilized Continuous Wavelet Transform (CWT) in conjunction with seismic attributes like RMS and Coherence to predict sand distribution in fluvial depositional systems. While RMS and Coherence attributes effectively identified fluvial systems at shallow depths, they failed to detect different fluvial elements at greater depths. In contrast, CWT successfully identified channels and other fluvial systems at deeper levels, demonstrating its advantage over traditional attributes. Similarly, Asim *et al*. (201) applied Short-Time Fourier Transform (STFT) to a 3D seismic dataset from Penobscot, Nova Scotia Offshore, Canada, and were able to determine the structures and lithology of a reservoir, highlighting the value of spectral analysis in reservoir characterization. This research aims to utilize Spectral Decomposition to enhance the identification of structural and stratigraphic traps, thereby reducing uncertainty and potential risks during drilling operations.

**Spectral Decomposition**

Spectral Decomposition (SD) is a valuable imaging tool that breaks down seismic signals into their individual frequency components, enabling geologists and geophysicists to gain a higher-resolution understanding of subsurface geology. This technique was pioneered by researchers at BP and Amoco in the 1990s, led by Gregory Partyka. By analyzing these frequency components, SD facilitates more detailed interpretation of subsurface structures and features**.**

It is a sophisticated algorithm that transforms seismic data from the time domain to the frequency domain, enabling detailed interpretation of subsurface features. By analyzing amplitude responses at various frequencies, it can illuminate formations at their tuning thickness, revealing geological features like channels and complex faulted areas that may not be visible on conventional amplitude sections (Torrado *et al*., 2014). This technique uses mathematical algorithms like Discret Fourier Transform (DFT), Continue Wavelet Transform (CWT), Stockwell - Transform (S-Transform), and Matching Pursuit Decomposition (MPD) to convert seismic data into frequency volumes, allowing for detailed seismic interpretation. The choice of algorithm depends on the interpretation objective, with each method having its strengths and limitations. For example, DFT uses a fixed time window, while CWT offers high spectral resolution but decreased temporal resolution. MPD provides good temporal and spectral resolution without windowing but is computationally expensive (Chopra and Marfurt, 2015).

According to Chopra and Marfurt (2015), the Continuous Wavelet Transform (CWT) with a Morlet wavelet mother function is a robust approach for spectral decomposition, outperforming other mother wavelets like Mexican-hat, Gaussian, and Shannon wavelet. By applying spectral decomposition, a series of seismic frequency slices can be generated, producing amplitude maps that can be co-blended to create high-resolution images of reservoir boundaries, lithological heterogeneity, and interval thickness. This approach provides more detailed information than conventional full-band seismic displays.

**Fourier Transform (FT)**

The Fourier Transform (FT) is a method that converts seismic data from the time domain to the frequency domain, where geological structures of interest are often more visible. In some cases, features are encoded in the frequency domain and not apparent in the time domain. FT is applied in both processing and interpretation to decompose seismic data into frequency components. During processing, FT helps separate signal from noise, allowing for filtering and noise reduction. The transformed data can then be converted back to the time domain, free from noise (Saadatinejad & Hassani 2013). FT is a powerful tool for both data processing and interpretation, offering flexibility and efficiency in frequency domain calculations. Seismic data is represented as a sum of sinusoids, and the Forward Fourier Transform analyzes seismic traces into their sinusoidal components (Yilmaz, 2001).

Seismic data, whether in the time or frequency domain, can be represented as a discrete sum of sinusoids. This representation allows for the analysis of seismic signals in terms of their frequency components as shown in Figure 1.

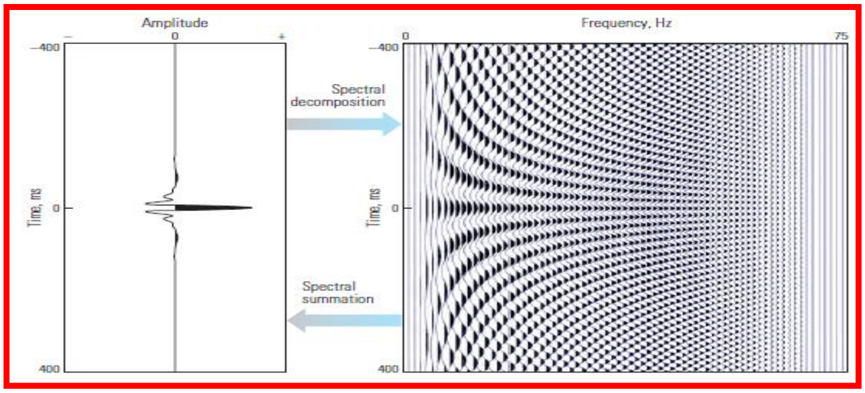


Figure 1: The Decomposition of Seismic Signal in to its Various Frequency components
Source: Victor *et al.*, 2012

The Fourier transform (FT) $\int(w)$ of a signal is the inner product of the signal with the basis function $e^{iwt}$ i.e.

$$\int(w) = < f(t), e^{iwt} > = \int_{-\infty}^{\infty} f(t)\, e^{-iwt} dt. \quad (1)$$

From Euler's theorem

$$e^{iwt} = \cos(wt) + i\sin(wt). \quad (2)$$

The Fourier analysis is based on sine and cosine trigonometric functions (Sinha *et al.*, 2005). It works by cross-correlating seismic data with suites of sine and cosine functions at specific frequencies (Chopra *et al.*, 2007). Each cross-correlation result represents a frequency component. FT is reversible, allowing for seamless conversion between the time and frequency domains. This reversibility enables transformation of signals from the time domain to the frequency domain and vice versa using the given equation below;

$$X(f) = \int_{-\infty}^{\infty} x(t).\, e^{-i2\pi ft} dt. \quad (3)$$

And can move back to the time axis from the frequency axis using the equation;

$$x(t) = \int_{-\infty}^{\infty} X(f).\, e^{i2\pi ft} df. \quad (4)$$

In equations 3 and 4, the variables are defined as follows: $t$ denotes time, $f$ represents frequency, $x(t)$ signifies the signal in the time domain, and $X(f)$ represents the signal in the frequency domain. This notation convention allows for clear distinction between the two signal representations. Equation 3 defines the Fourier transform of $x(t)$, while Equation 4 defines the inverse Fourier transform of $x(t)$, enabling transformation between the time and frequency domains (Polikar, 1994).

Fourier Transform (FT) provides frequency component information of a signal, revealing the amount of each frequency present. However, it lacks temporal information, failing to indicate when these frequency components occur. This limitation is insignificant for stationary signals, where frequency content remains constant over time. In contrast, seismic data is a non-stationary signal, where frequency content varies with time, making it essential to know when specific frequencies occur. Stationary signals have frequency components that exist at all times, eliminating the need for temporal information (Polikar, 1994).

To grasp the concept of signal stationarity and non-stationarity, let's examine the work of Polikar (1994). Specifically, Figure 2 illustrates a stationary signal generated using the following equation:

$$x(t) = \cos(2\pi 10t) + \cos(2\pi 25t) + \cos(2\pi 50t) + \cos(2\pi 100t) \quad (5)$$

This example helps demonstrate the characteristics of stationary signals, where frequency content remains constant over time. This stationary signal comprises frequency components of 10, 25, 50, and 100 Hz, consistently present at every time interval (Figure 2). The signal's periodic nature, repeating every 200 ms, further confirms its stationarity. The Fourier transform (Figure 3) accurately captures the four spectral components corresponding to these frequencies. In contrast, the non-stationary signal (Figure 4) exhibits time-varying frequency components. Upon closer inspection, we observe distinct frequency ranges: 100 Hz (0-300 ms), 50 Hz (300-600 ms), 25 Hz (600-800 ms), and 10 Hz (800-1000 ms). This signal's frequency content changes over time, defining its non-stationary nature.

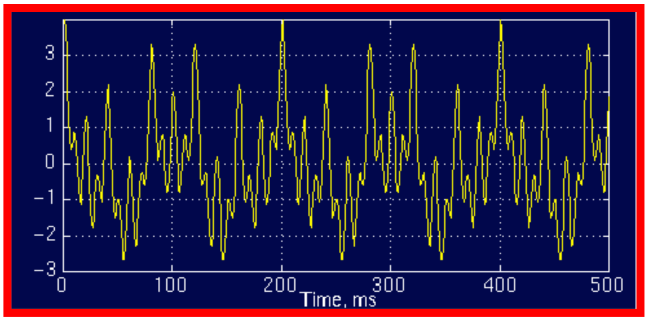


Figure 2: Generation of a stationary signal
Source: Polikar, (1994)

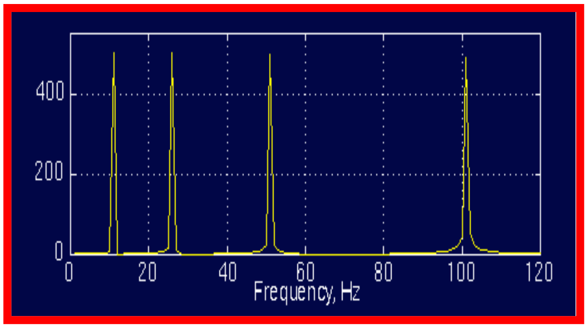


Figure 3: Fourier Transform of the Stationary Signal in Figure 2. Source: Polikar (1994).

In Figure 5, the higher frequency components exhibit higher amplitudes due to their longer duration (300 ms) compared to the lower frequency components (200 ms). However, these amplitude differences can be normalized and may not significantly impact analysis. Both signals' Fourier Transforms (Figures 3 and 5) display four identical frequency peaks at 10, 25, 50, and 100 Hz, despite their distinct time-domain representations (Figures 2 and 4). The stationary signal has these frequencies consistently, while the non-stationary signal has them at different time intervals. This similarity in FT spectra highlights a limitation: Fourier Transform is not ideal for analyzing non-stationary signals, such as seismic data, as it only provides overall frequency behavior without temporal information (Sinha *et al.*, 2005; Chakraborty and Okaya, 1995).

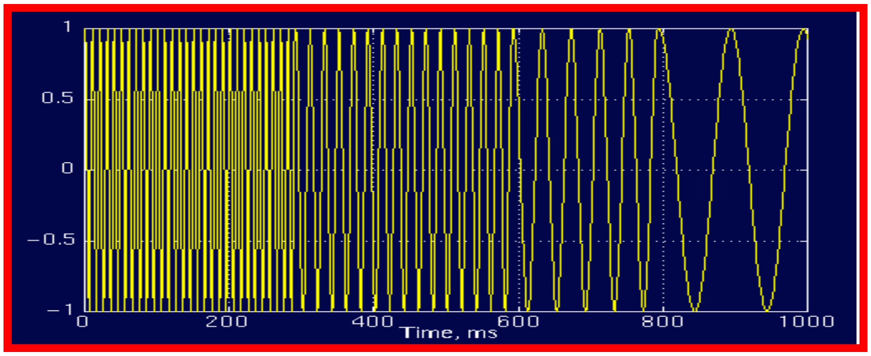


Figure 4: Plot of a Signal having 4 Frequency Components at Different Time Interval
Source: Polikar, (1994)

The Fourier Transform (FT) of the non-stationary signal is shown in Figure 5, where the ripples or artifacts are likely due to the abrupt transitions between different frequency components.

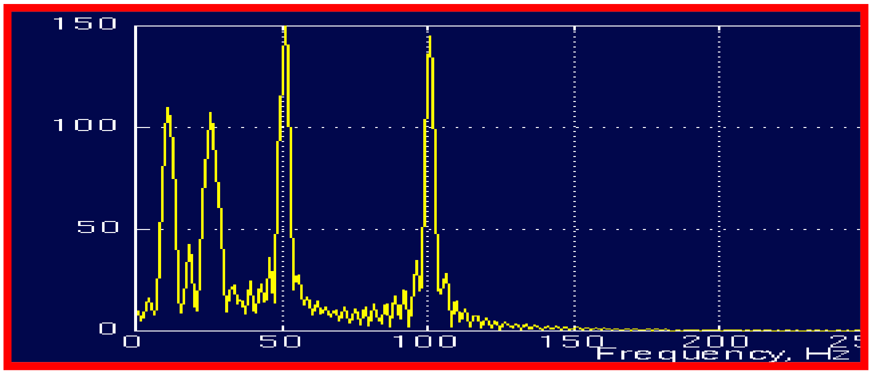


Figure 5: Fourier Transform of the Non-Stationary Signal shown in Figure 4
Source: Polikar, (1994).

According to Polikar (1994), Fourier Transform (FT) is suitable for non-stationary signals only when the goal is to identify the existing frequency components, without concern for their timing. However, when time information is essential, FT falls short. FT provides frequency content, but not the temporal distribution of these frequencies. Notably, non-stationary signals often contain stationary segments, as illustrated in Figure 4. By applying a window function to these stationary segments, FT can be effectively used. The Short-Time Fourier Transform (STFT) builds on this concept by dividing non-stationary signals into smaller stationary segments and applying FT to each (Shorollahi *et al.,* 2013). This involves multiplying the signal segments with a chosen window function and then performing FT, as depicted in Figure 6. The resulting time-frequency representation is known as a spectrogram (Cohen, 1995; Sinha *et al.*, 2005).

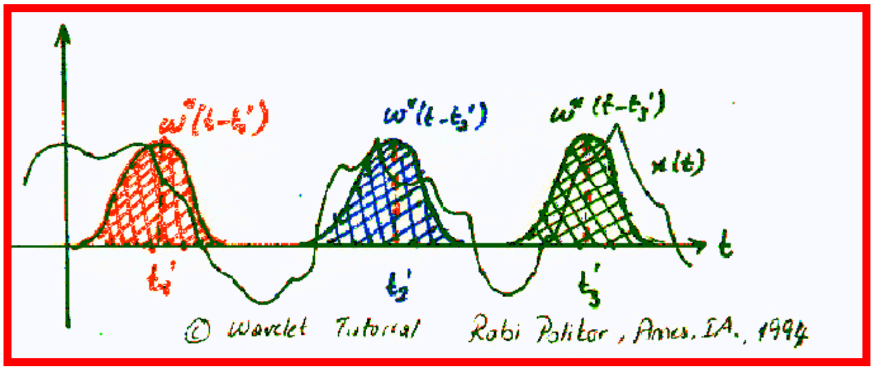


Figure. 6: Windowing of a Stationary Signal
Source: Polikar, (1994)

The Short-Time Fourier Transform (STFT) involves windowing a non-stationary signal into smaller, supposedly stationary segments, and applying the Fourier Transform (FT) to each segment. Unlike FT, which analyzes the entire signal at once, STFT uses a window function to localize the analysis in time. The window function, such as the Gaussian-like functions shown in Figure 2.6, is designed to capture a specific portion of the signal. Commonly used window functions include tapered rectangular, untapered rectangular, and Gaussian windows. By shifting the window function in time, STFT generates a series of Fourier Transforms, each corresponding to a different time interval. Mathematically, STFT can be represented as the dot product of the seismic data $f(t)$ with a time-shifted window function ∅ (t) (Sinha et al., 2005). This can be expressed mathematically as;

$$STFT(\omega,\tau) = \langle f(t), \emptyset(t-\tau)e^{iwt}\rangle = \int f(t), \overline{\emptyset}(t-\tau)e^{-iwt}dt. \quad (6)$$

In Equation 6, $f(t)$ represents the non-stationary seismic signal, and ∅ (t) represents the window function. The equation illustrates that the Short-Time Fourier Transform (STFT) of a non-stationary signal is obtained by multiplying the signal with a window function and then applying the Fourier Transform (FT) (Polikar, 1994). Notably, the length of the window function in STFT remains fixed for all frequency components, as depicted in Figure 7.

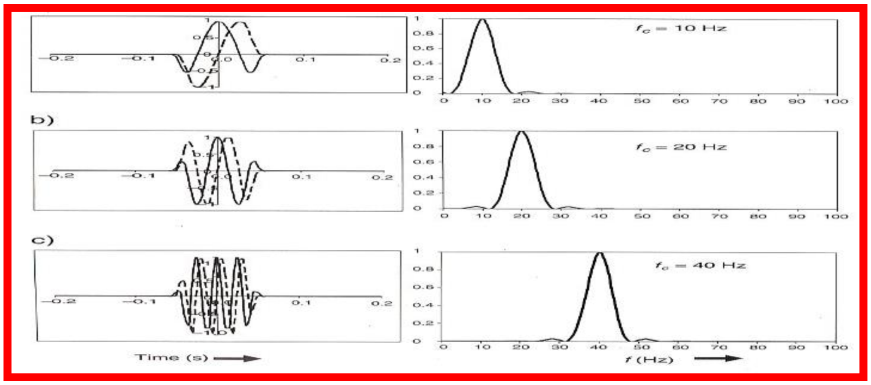


Figure7: Seismic wavelets and their Corresponding Frequency Spectral for Different Frequency Value
Source: (Chopra and Marfut, 2007)

Figure 8 demonstrates the effectiveness of applying Short-Time Fourier Transform (STFT) to a time slice for delineating a meandering channel body. Initially, the channel body within the red loop is not clearly visible on the original time slice. However, after applying STFT, the channel becomes more pronounced, showcasing the technique's ability to enhance imaging of complex geological features.

**Continuous Wavelet Transform**

The Continuous Wavelet Transform (CWT) offers an alternative approach to time-frequency signal analysis, widely used in various scientific and technical fields. This spectral decomposition (SD) algorithm generates a time-scale map of seismic signals (Sinha *et al.,* 2005; Dimri *et al.,* 2005). CWT utilizes dilation and translation of a mother wavelet to produce the time-scale map, where scale corresponds to frequency bands. As the wavelet dilates, its temporal support changes, affecting frequency resolution: increased time support decreases frequency resolution (lower frequencies), while decreased time support increases frequency resolution (higher frequencies). This trade-off between time and frequency resolution is a key characteristic of CWT. Unlike the Short-Time Fourier Transform (STFT), which provides a time-frequency spectrum, CWT generates a time-scale signal map, where scale is inversely related to the central wavelet frequency.

When applying Continuous Wavelet Transform (CWT) for spectral decomposition, selecting a suitable mother wavelet is crucial, as it significantly impacts the transform's outcome (Saadatinejad and Hassani, 2013). Commonly used mother wavelets include Morlet, Mexican-hat, and Gaussian wavelets. The choice of mother wavelet plays a vital role in determining the effectiveness of the CWT algorithm.

The choice of mother wavelet in Continuous Wavelet Transform (CWT) significantly influences the outcome. Using a Gaussian wavelet yields results similar to Short-Time Fourier Transform (STFT), making it suitable for stratigraphic studies. In contrast, the Morlet wavelet is more effective for structural and hydrocarbon potential studies. The Mexican-hat wavelet produces average results compared to Gaussian and Morlet wavelets (Saadatinejad and Hassani, 2013). Unlike the Short-Time Fourier Transform (STFT) with fixed window length, CWT's window length varies with frequency, resulting in improved temporal resolution at high frequencies and enhanced frequency resolution at low frequencies (Chopra and Marfurt, 2015).

As shown in Figure 9, the CWT window adapts to frequency, yielding high frequencies for sharper temporal resolution and low frequencies for sharper frequency resolution. This adaptive windowing enables CWT to effectively capture transient events and subtle frequency variations.

According to Chopra and Marfurt (2007), the window functions used in wavelet transform decomposition typically have the form of a mother wavelet, which is a localized, oscillating function that can be scaled and translated to capture signal characteristics at different resolutions. These wavelets are designed to capture specific patterns and features in signals, allowing for effective decomposition and analysis. The window function is of the form;

$$w(k\Delta t) \equiv w_k = \frac{1}{\sqrt{\delta}} exp\left[\frac{-(k\Delta t)^2}{2\delta^2}\right] \qquad (7)$$

Where δ is the width of the wavelet. In CWT, the window selected is not fixed; it varies with frequency, i.e., shorter windows for high frequencies and longer windows for lower frequencies, as shown in Figure 9 (Chopra and Marfurt, 2007). In CWT, the signal is multiplied by the window function. The length of the window function is not constant; the length of the temporal window changes according to the required frequency resolution (Shorollahi *et al.*, 2013).

According to Sinha et al. (2005), the Continuous Wavelet Transform (CWT) is defined as the dot product of a family of mother wavelets, $\bar{\psi}$ (δ,τ) $(t)$, with the seismic data, $f(t)$. Mathematically, this is expressed as:

$$F_W(\delta,\tau) = \langle f(t), \psi_{\delta,\tau}\rangle = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{\delta}}\bar{\psi}(\frac{t-\tau}{\sigma})dt \qquad (8)$$

In the equation above, $\bar{\psi}$ represents the complex conjugate of ψ. The resulting transform, $F_W(\delta,\tau)$ is a time-scale map, commonly referred to as the scalogram. Here, σ and τ denote the dilation and translation parameters, respectively. The term $\frac{1}{\sqrt{\delta}}$ serves as a normalization factor, ensuring that the energy level remains consistent before and after the transformation process.

A spectrogram can be computed for a chirp signal, as shown in Figure 10, which features two hyperbolic frequency sweeps. These sweeps can be accurately visualized when decomposed in the frequency domain. By applying the Continuous Wavelet Transform (CWT) algorithm with a Morlet wavelet, the chirp signal can be effectively decomposed, resulting in the spectrogram shown in Figure 11, obtained using equation 8. Figure 11 shows an erroneous decrease in energy with frequency for both trends. However, using a complex wavelet and a modified Continuous Wavelet Transform (CWT) algorithm, a more accurate representation of the chirp signal's spectrum can be obtained, as seen in Figure 12. This highlights that the effectiveness of the CWT algorithm depends on the choice of mother wavelet. For a comprehensive discussion on wavelets for Continuous Wavelet Transform (CWT), the reader is referred to Ngeri *et al.* (2018).

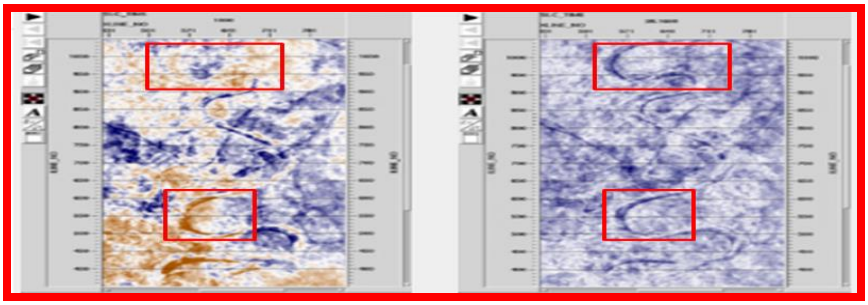

Figure 8: Left Image showing Time Slice imaging meandering channel. Right image showing the application of SD on time slice. Red loop on the right image shows better imaging of the channel body. Source: [http://excelgeo.com/excel-software/spectral-decomposition/](http://excelgeo.com/excel-software/spectral-decomposition/)

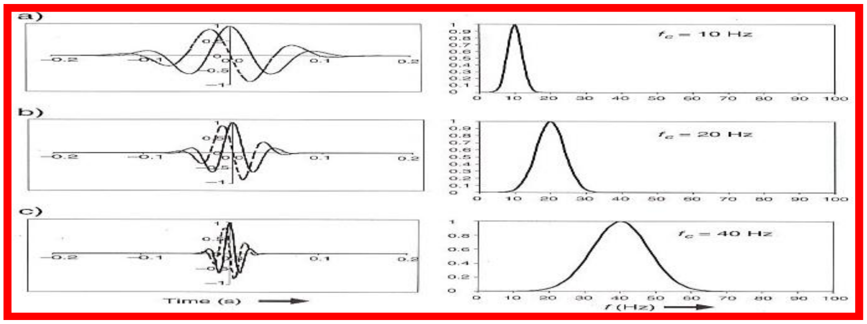


Figure 9: Seismic Wavelets and their Corresponding Frequency Spectral for Different Frequency Value. Source: Chopra and Marfut, (2007)

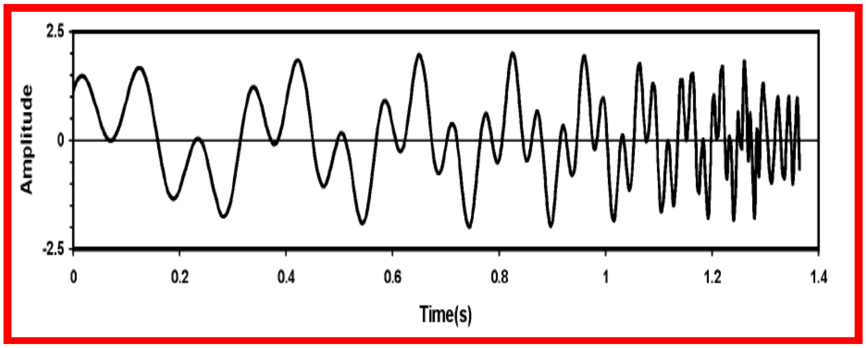


Figure 10: Chirp Signal Consisting of two know Hyperbolic Sweep
Source: Sinha *et al.*, 2005.

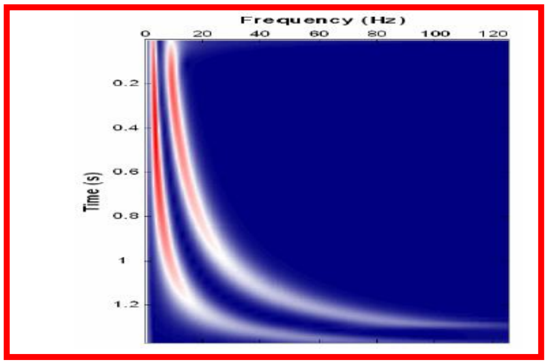


Figure 11: CWT Spectrum of the Chirp Signal. Source: Sinha *et al.*, 2005

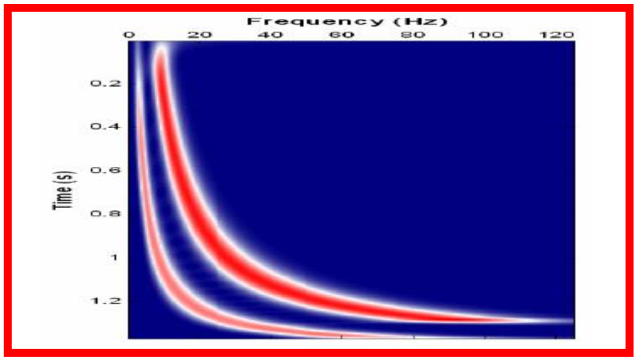


Figure 12: CWT Spectrum of a Chirp Signal using Complex Wavelet. Source: Sinha *et al.*, 2005

**Stockwell - Transform (S-Transform)**

The S-Transform, developed by Stockwell et al. (1996), extends the Continuous Wavelet Transform (CWT) method for Spectral decomposition (SD). It utilizes a moving and scalable Gaussian window, offering desirable characteristics such as phase information, which provides valuable spectral insights not present in CWT. This phase information effectively makes S-Transform a phase correction of CWT. As noted by Zabihi and Siahkoohi (2006), S-Transform can be viewed as a hybrid approach combining elements of Short-Term Fourier Transform (STFT) and CWT.

The Short-Time Fourier Transform (STFT) of a signal $f(t)$ is mathematically represented by Equation (6). Where $\overline{\emptyset}(t-\tau)$represents the window function, and τ and ω denote the time of spectral localization and frequency, respectively. The S-Transform algorithm can be derived from Equation (6) by substituting the window function with a Gaussian function, expressed as;

$$\overline{\emptyset}(t-\tau) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(t^2 f^2)}{2}} \quad (9)$$

Substituting Equation (9) into Equation (6) gives;

$$S(\tau,\omega) = STFT(\tau,\omega) = \int_{-\infty}^{\infty} f(t) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(t^2 f^2)}{2}} e^{-iwt} dt \quad (10)$$

Equation (10) reveals that the S-Transform is a special case of the Short-Time Fourier Transform (STFT) that utilizes a Gaussian window function. Studies by researchers like Zabihi and Siahkoohi (2006) have compared the spectral analysis capabilities of STFT, Continuous Wavelet Transform (CWT), and S-Transform in detecting hydrocarbons in reservoirs, aiming to determine the most effective method for signal decomposition (SD).

**Matching Pursuit (MP) Decomposition**

The Matching Pursuit (MP) algorithm, introduced by Mallat and Zhang (1993), aims to extract sparse signals from time series data, such as seismic traces. This signal decomposition (SD) technique produces high-resolution time-frequency spectra. The MP algorithm decomposes reflection seismic data into a series of scaled wavelets, selecting them from a predefined wavelet dictionary, as demonstrated in studies by Miao and Cheadle (1998) and Wen *et al.* (2015). A wavelet dictionary is a comprehensive collection of wavelets that spans the entire range of time, frequency, scale, and phase indices. This extensive library enables the representation of each component of a seismic signal, thereby enhancing spectral resolution (Miao *et al.*, 2007).

The Matching Pursuit (MP) algorithm utilizes various wavelet dictionaries to decompose seismic traces, including Morlet, Ricker, and mixed-phase wavelets. Among these, the Morlet wavelet is the most commonly used due to its close approximation to seismic wavelets. For effective decomposition, the wavelet dictionary should resemble the seismic trace, and the Morlet wavelet's similarity to seismic wavelets makes it a preferred choice.

According to Morlet *et al.* (1982) a Morlet wavelet is defined as;

$$m(t) = exp\left[-\left(\frac{In2}{\pi^2}\right)\frac{{\omega_m}^2(t-u)^2}{\sigma^2}\right] exp[i(\omega_m(t-u)+\phi)] \quad (11)$$

Where $\omega_m$represents the mean frequency, $u$ is the time delay, $\phi$ is the phase angle, and σ is the scale parameter controlling the wavelet width. The scale parameter is crucial for the constituent wavelet. Notably, the scale parameter is a key differentiator between Matching Pursuit and other spectral decomposition methods.

According to Wang (2007), generating a suitable Morlet wavelet for seismic signal decomposition requires determining five key parameters through complex trace analysis: amplitude (a), time delay ($u$), scale ($\sigma$), mean frequency ($\omega_m$), and phase ($\phi$). When these parameters are accurately determined, the resulting Morlet wavelet closely matches the seismic wavelet in the data. This similarity enables Matching Pursuit to produce a high-quality time-frequency decomposition, effectively extracting valuable information from the seismic data (Tianzi and Wei, 2012).

Once the Morlet wavelet is generated, it is used to decompose the seismic trace into constituent wavelets. After decomposition, the seismic trace is represented as a series of wavelets, $g_{\gamma_n}(t)$, for n=0,1,2,3…N-1. This decomposition yields a clear and detailed representation of the energy distribution in the time-frequency plane. According to Wen et al. (2015), the Matching Pursuit (MP) algorithm operates by first identifying seismic events that match wavelets stored in a dictionary. The best-matching wavelet is cross-correlated with the 3D data, and its projection is subtracted from the data. This process is repeated, with the wavelet dictionary cross-correlated with the residual, and the best-correlated wavelet projection eliminated, until the residual energy falls below a predefined threshold (Mallat and Zhang, 1993).

Wen et al. (2015) summarize the Matching Pursuit (MP) algorithm in the following steps: (1) define a wavelet dictionary comprising various wavelets, such as Morlet wavelets; (2) correlate each wavelet with the seismic trace in the time domain to identify the best-matching wavelet for the strongest reflection; (3) subtract the best-matching wavelet while recording the reflection coefficient; and (4) repeat steps 2-3 on the residual plot until the residual energy falls below a user-defined threshold. As noted by Mallat and Zhang (1993), the MP algorithm is a greedy algorithm that iteratively selects the most suitable waveform to approximate the signal. This process is exemplified in Figure 13, which illustrates the decomposition of a synthetic trace into its frequency domain using the MP algorithm.

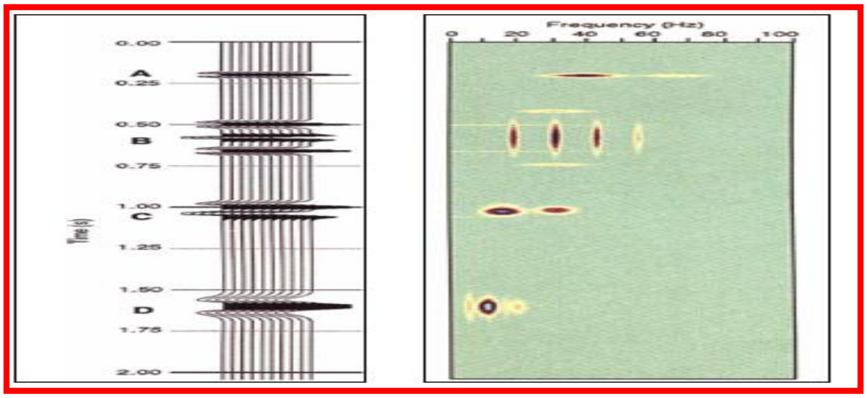

Figure 13: A Synthetic Trace Decomposed into its Frequency Domain using MP Decomposition Algorithm
Source: Chakraborty and Okaya (1995)

## MATERIALS AND METHODS

This study utilized Petrel and OpendTect 4.6.0 software packages to analyze a secondary dataset from Shell Petroleum Development Company (SPDC). The research was conducted in three stages. Initially, conventional seismic interpretation methods were applied, involving data analysis, noise reduction through filtering, horizon picking to generate surfaces, and fault identification from amplitude sections on the 3D seismic volume. In the second stage, Spectral Decomposition was employed to enhance the visibility of structural and stratigraphic traps, revealing features that were not apparent through conventional interpretation. The results showed that Spectral Decomposition outperformed conventional methods in delineating faults and channels. Finally, in the third stage, a detailed interpretation of the results was carried out. A workflow diagram illustrating the methodology is presented in Figure 14.

## RESULTS AND DISCUSSION

The results of this study demonstrate the effectiveness of Continuous Wavelet Transform (CWT)-based Spectral Decomposition as a complementary technique to conventional seismic interpretation for enhancing subtle structural and stratigraphic features. The analysis of both land and marine 3D seismic datasets indicates that features that are poorly expressed or difficult to identify on conventional seismic displays become more clearly defined after transformation into the time-frequency domain. The improvement is particularly evident in the delineation of subtle faults, sub-seismic fault expressions, and buried meandering channels.

The improved performance of Spectral Decomposition observed in this study is consistent with the fundamental principle of time-frequency analysis. Conventional seismic amplitude displays represent the seismic response primarily in the time domain, whereas spectral decomposition separates the seismic signal into its constituent frequency components. This enables geological features whose seismic responses are concentrated within particular frequency ranges to become more distinguishable. Sinha et al. (2005) demonstrated that CWT provides a time-frequency representation without requiring the fixed analysis window associated with the Short-Time Fourier Transform (STFT), thereby providing improved localization of non-stationary seismic events. They further demonstrated the application of CWT spectral decomposition to subtle stratigraphic features and hydrocarbon-related seismic anomalies.

In the present study, the land seismic results provide strong evidence for the application of CWT to structural interpretation. Figure 15 shows that some faults are difficult to recognize directly from the conventional 2.5 s time slice and require considerable interpreter experience. Following Spectral Decomposition, however, the same faults become more clearly expressed within the identified circular areas. This indicates that the frequency-dependent characteristics of the seismic response provide additional information that is not readily apparent in the conventional amplitude representation.

The observation is particularly significant in Figure 16, where subtle and potentially sub-seismic fault expressions are poorly defined in the conventional 2.8 s time slice but become more conspicuous after CWT decomposition. This result is comparable with previous work demonstrating that frequency-dependent seismic attributes can preferentially highlight faults having different vertical displacements. Studies using CWT-based spectral decomposition have shown that major faults may be preferentially enhanced at lower frequencies, whereas smaller antithetic faults and subtle structural discontinuities may become more apparent at higher frequencies.

The results therefore suggest that the improved fault delineation observed in this research is not simply an enhancement of image brightness but reflects the ability of spectral decomposition to separate seismic responses according to their frequency content. Nevertheless, the term "sub-seismic fault" should be used carefully. Spectral decomposition does not necessarily resolve a geological feature that is completely below the fundamental seismic resolution limit. Rather, it can enhance weak seismic expressions associated with small-scale features that are poorly represented in the conventional seismic volume. This distinction is important when interpreting the results.

The marine seismic results demonstrate a complementary application of CWT for stratigraphic interpretation. In Figure 17a, Horizon H2 contains potential channel features, but their boundaries are poorly defined in the conventional horizon display. After application of CWT-based Spectral Decomposition, Figure 17b provides a substantially clearer representation of the channel geometry. The improved lateral continuity and definition of the channel boundaries facilitate interpretation of the depositional architecture.

This observation agrees with the findings of Ehirim and Akpan (2017), who applied CWT-based Spectral Decomposition to 3D seismic data from the Niger Delta. Their study demonstrated that frequency-amplitude slices generated using CWT could reveal stratigraphic variability and delineate reservoir sands that were less apparent from conventional seismic interpretation. The agreement between their results and the present study is particularly relevant because both investigations involve Niger Delta seismic data and demonstrate the usefulness of CWT for extracting geological information that is difficult to identify directly from conventional seismic displays.

The results obtained from the marine dataset are also consistent with the work of Aminu and Ojo (2018), who applied wavelet-based spectral decomposition to deep turbidite systems in the Niger Delta. Their study showed that spectral decomposition enhanced depositional features that were not apparent on conventional seismic amplitude displays, including linear channels, terminal splay lobes, sinuous channels and abandoned meander loops. The present study similarly demonstrates improved visualization of a meandering channel system, particularly in Figure 18, where the channel is only faintly expressed on the conventional 3 s time slice but becomes considerably more recognizable after CWT processing.

The present results also compare favorably with international studies of buried-channel systems. Kazemeini et al. (2009) demonstrated the usefulness of CWT for mapping channel deposits and detecting frequency-dependent anomalies in seismic data from the CO2SINK site in Germany. Their work showed that CWT can provide useful geological information associated with both low- and high-frequency components that may not be adequately represented in conventional seismic displays. Similarly, studies of channel reservoirs in Mexico have shown that spectral decomposition can reveal channels, thin-bed reflections and subtle faults that are difficult to interpret from conventional seismic data alone.

An important comparison can also be made with the study by Adizua and Lenyie (2023) on subsurface channels in the Niger Delta. Their research compared Fast Fourier Transform (FFT) and CWT spectral decomposition and found that the two methods did not enhance all geological features equally: FFT provided stronger enhancement of channels and crevasse splays, whereas CWT was particularly effective for major and minor fault delineation. The present study is consistent with the latter observation because CWT produced a marked improvement in the visualization of subtle faults in the land dataset. However, the present marine results additionally demonstrate that CWT can provide useful enhancement of channel geometry and continuity. This suggests that the effectiveness of a particular decomposition method may depend on the seismic character, frequency content, depositional setting and geological objective of the investigation.

Further support comes from Durogbitan et al. (2023), who applied both STFT and CWT spectral decomposition to identify subtle stratigraphic baffles in the offshore Niger Delta. Their study showed that spectral decomposition could reveal features that were not identified through conventional attribute analysis, including potential faults, lateral lithological variations and shale baffles responsible for reservoir compartmentalization. This is important in relation to the present study because it demonstrates that the value of spectral decomposition extends beyond simple visualization; frequency-dependent seismic information can provide additional evidence for interpreting subtle geological heterogeneities and reservoir architecture.

The combined land and marine results therefore demonstrate two major applications of CWT-based Spectral Decomposition. In the land dataset, the principal improvement is associated with structural interpretation, particularly the enhancement and delineation of major, minor and subtle fault expressions. In the marine dataset, the major improvement is associated with stratigraphic interpretation, particularly the visualization and delineation of buried and meandering channel systems. This dual application distinguishes the present study from investigations that concentrate primarily on either structural or stratigraphic interpretation.

Overall, the results support previous investigations showing that Spectral Decomposition is most effective when used as a complement to, rather than a replacement for, conventional seismic interpretation. Conventional seismic sections remain essential for understanding reflection continuity, structural relationships and the overall geological framework, while CWT provides an additional frequency-dependent perspective that can reveal subtle features. The comparison with previous studies further demonstrates that the observed improvements are consistent with the established capability of CWT-based spectral decomposition to enhance geological features that are weakly expressed in conventional seismic data.

A major implication of this study is that the integration of conventional interpretation with CWT-based Spectral Decomposition can improve the confidence of seismic interpretation in complex depositional and structural settings. The technique is particularly useful in areas where subtle faults and stratigraphic bodies are important to reservoir characterization but are poorly resolved in conventional seismic displays. However, the enhanced features should always be interpreted within the geological and seismic-resolution framework and, where possible, validated using well information, additional seismic attributes or independent geological evidence.

## CONCLUSION

This study highlights the effectiveness of Spectral Decomposition in improving seismic data interpretation by revealing subtle geological features, including faults, channels, and point bars. Importantly, it enables the identification of sub-seismic faults that are frequently missed in conventional time-slice analyses. Through the application of Spectral Decomposition, geologists and geophysicists can greatly enhance well placement accuracy, allowing them to focus on the most prospective zones for exploration and production.

## REFERENCES

Ambati, V., Mahadasu, N. B., & Nair, R. R. (2021). Reservoir wellbore stability analysis and weak zones identification using the 1d mem, swelling tests and ucs: A case study from mumbai offshore, India. *Arabian Journal for Science and Engineering, 47*, 1-23. DOI.10.1007/s13369-021-05530-w

Aminu, M. B., & Ojo, S. B. (2018). Application of spectral decomposition and neural networks to characterise deep turbidite systems in the outer fold and thrust belt of the Niger Delta. *Geophysical Prospecting, 66*, 736–752. https://doi.org/10.1111/1365-2478.12569

Ashique, S., & Samiranjan, B. (2010). Use of ant-track volume in horizontal well placement. *8th Biennial International Conference & Exposition on Petroleum Geophysics*, Paper 296.

Asim, S., Ahmad, S., Zhu, P., Naseer, M. T., & Butt, M. (2016). Spectral decomposition application for analyzing the structure and the reservoir potential: A case study of Penobscot, Nova Scotia offshore, Canada. *Arabian Journal of Geosciences, 9*, 66. https://doi.org/10.1007/s12517-015-2168-x

Castagna, J. P., Sun, S. and Siegfried, R. W., (2003). Instantaneous spectral analysis: Detection of low-frequency shadows associated with hydrocarbons. *The Leading Edge*, 22(2), 120-127. https://doi.org/10.1190/1.1559038

Chakraborty, A., & Okaya, D. (1995). Frequency-time decomposition of seismic data using wavelet-based methods. *Geophysics, 60*(6), 1906–1916. https://doi.org/10.1190/1.1443922

Chopra, S. and Marfurt K, J., (2007). Seismic Attributes for Prospect Identification and Reservoir Characterization. SEG Geophysical Development Series No. 11. 45 - 72. https://doi.org/10.1190/1.9781560801900

Chopra, S., & Marfurt, K. J. (2015). Choice of mother wavelets in CWT spectral decomposition. *SEG Technical Program Expanded Abstracts 2015*, 2957–2961. https://doi.org/10.1190/segam2015-5852193.1

Chopra, S., & Marfurt, K. J. (2007). *Seismic Attributes for Prospect Identification and Reservoir Characterization*. SEG Geophysical Development Series No. 11. Society of Exploration Geophysicists. https://doi.org/10.1190/1.9781560801900

Cohen, L. (1995). *Time-Frequency Analysis*. Prentice Hall.

Dimri, V. P., Vedanti, N., & Chattopadhyay, S. (2005). Fractal analysis of aftershock sequence of Bhuj earthquake – A wavelet based approach. *Current Science, 88*, 1617–1620.

Durogbitan, A., Simon, E., Auduson, A., Ekene, O., & Collins, I. (2023). Use of spectral decomposition in identifying stratigraphic baffles below seismic resolution: A case study of UTB field, offshore Niger Delta. *Journal of Applied Geophysics, 217*, 105193. https://doi.org/10.1016/j.jappgeo.2023.105193.

Ehirim, C. N., & Akpan, A. S. (2017). Continuous Wavelet Transform Based Spectral Decomposition of 3D Seismic Data for Reservoir Characterization in Oyi Field, SE Niger Delta. *American Journal of Applied Sciences, 14*(8), 766–771. https://doi.org/10.3844/ajassp.2017.766.771

Holdaway, K. R., & Irving, D. H. B. (2017). *Enhance Oil & Gas Exploration with Data-Driven Geophysical and Petrophysical Models*. John Wiley & Sons. https://doi.org/10.1002/9781119394228

Kazemeini, S. H., Juhlin, C., Zinck-Jørgensen, K., & Norden, B. (2009). Application of the continuous wavelet transform on seismic data for mapping of channel deposits and gas detection at the $CO_2$SINK site, Ketzin, Germany. *Geophysical Prospecting, 57*(1), 111–123. https://doi.org/10.1111/j.1365-2478.2008.00723.x

Kobr, M. (2021). Geophysical well logging. In H. K. Gupta (Ed.), *Encyclopedia of Solid Earth Geophysics*. Springer, Cham. https://doi.org/10.1007/978-3-030-58631-7_173

Lai, J., Wang, G., Fan, Q., Pang, X., Li, H., Zhao, F., Li, Y., Zhao, X., Zhao, Y., Huang, Y., Bao, M., Qin, Z., & Wang, Q. (2022). Geophysical well-log evaluation in the era of unconventional hydrocarbon resources: A review on current status and prospects. *Surveys in Geophysics, 43*(3), 913–957. https://doi.org/10.1007/s10712-022-09705-4

Mallat, S. G., & Zhang, Z. (1993). Matching pursuits with time-frequency dictionaries. *IEEE Transactions on Signal Processing, 41*(12), 3397–3415. https://doi.org/10.1109/78.258082

Miao, X., & Cheadle, S. (1998**).** High resolution seismic data analysis by wavelet transform and matching pursuit decomposition. *Geo-Triad, CSEG/CSPG/CWLS Joint Convention*, 31–32.

Miao, X., Todorovic-Marinic, D., & Klatt, T. (2007). Enhancing seismic insight by spectral decomposition. *SEG Technical Program Expanded Abstracts 2007*, 1437–1441. https://doi.org/10.1190/1.2792768

Mirza, N. A., Rowell, P., & Sriburee, S. (2014). Detection of fluvial sand systems using seismic attributes and continuous wavelet transform spectral decomposition: Case study from the Gulf of Thailand. *Marine Geophysical Research, 35*(2), 105–123. https://doi.org/10.1007/s11001-014-9213-0

Morlet, J., Arens, G., Fourgeau, E., & Giard, D. (1982). Wave propagation and sampling theory—Part I: Complex signal and scattering in multilayered media. *Geophysics, 47*(2), 203–221. https://doi.org/10.1190/1.1441328

Ngeri, A. P., Uko, E. D., and Tamunobereton-ari, I. (2018). The Choice of Mother Wavelet in the Application of Continuous Wavelet Transform Method of Spectral Decomposition in Field 'A' in Central Niger Delta. *Asian Journal of Applied Science and Technology (AJAST)*, 2 (4), 303-314.

Ngeri, A.P., O.A. Davies, Dieokuma Tamunosiki. (2024). Application of Coherence Attribute For Prospect Identification. *Journal of Scientific and Engineering Research*, 2024, 11(8):125-131.

Ngeri, A.P., Tamunobereton-ari, I. & Amakiri, A.R.C. (2015). Ant-Tracker Attributes: An Effective Approach to Enhancing Fault Identification and Interpretation. *IOSR Journal of VLSI and Signal Processing (IOSR-JVSP).*5(6), Ver. II, 67-73 E-ISSN: 2319 – 4200, P-ISSN No. : 2319 – 4197. https://doi.org/10.9790/4200-05626773

Partyka, G., Gridley, J., & Lopez, J. (1999). Interpretational applications of spectral decomposition in reservoir characterization. *The Leading Edge*, *18*(3), 353–360. https://doi.org/10.1190/1.1438295

Peyton, L., Bottjer, R., & Partyka, G. (1998). Interpretation of incised valleys using new 3-D seismic techniques: A case history using spectral decomposition and coherency. *The Leading Edge, 17*(10), 1294–1298. https://doi.org/10.1190/1.1438127

Polikar, R. (1994). The Engineer's Ultimate Guide to Wavelet Analysis. *Amed*. 1 - 79.

Saadatinejad, M. R., & Hassani, H. (2013). Application of wavelet transform for evaluation of hydrocarbon reservoirs: Example from Iranian oil fields in the north of the Persian Gulf. *Nonlinear Processes in Geophysics, 20*(2), 231–238. https://doi.org/10.5194/npg-20-231-2013

Shorollahi, E., Zargar, G., & Riahi, M. A. (2013). Using continuous wavelet transform and short-time Fourier transform as spectral decomposition methods to detect stratigraphic channel in one of the Iranian south-west oil fields. *International Journal of Science and Emerging Technologies*, 5(5), 291–299.

Sinha, S., Routh, P. S., Anno, P. D., & Castagna, J. P. (2005). Spectral decomposition of seismic data with continuous-wavelet transform. *Geophysics, 70*(6), P19–P25. https://doi.org/10.1190/1.2127113

Stockwell, R. G., Mansinha, L., & Lowe, R. P. (1996). Localization of the complex spectrum: The S transform. *IEEE Transactions on Signal Processing*, 44(4), 998–1001. https://doi.org/10.1109/78.492555

Zhao, T., & Song, W. (2012). An application of matching pursuit time-frequency decomposition method using multi-wavelet dictionaries. *Petroleum Science*, 9(3), 310–316. https://doi.org/10.1007/s12182-012-0214-9

Torrado, L., Mann, P., & Bhattacharya, J. (2014). Application of seismic attributes and spectral decomposition for reservoir characterization of a complex fluvial system: Case study of the Carbonera Formation, Llanos foreland basin, Colombia. *Geophysics*, 79(5), B221–B230. https://doi.org/10.1190/geo2013-0429.1

Victor, A. Taha, N.D. Andrew, B.S. Michael, J.S. Brian, T. Ole, V. & Gillian, W., (2012). Seismic Detection of Subtle Faults and Fracture. *Oilfield* Review Summer, 24, no 2, 28 – 43.

Wang, Y. (2007). Seismic time-frequency spectral decomposition by matching pursuit. *Geophysics*, 72(1), 13–20. https://doi.org/10.1190/1.2387109

Wen, X., Zhang, B., Pennington, W., & He, Z. (2015). Relative P-impedance estimation using a dipole-based matching pursuit decomposition strategy. *Interpretation*, 3(4), T197–T206. https://doi.org/10.1190/INT-2015-0035.1

Song, Y., Li, Z., Jiang, Z., Luo, Q., Liu, D., & Gao, Z. (2017). Progress and development trend of unconventional oil and gas geological research. *Petroleum Exploration and Development*, 44(4), 638–648. https://doi.org/10.11698/PED.2017.04.18

Yilmaz, Ö. (2001). *Seismic data analysis: Processing, inversion, and interpretation of seismic data*. Investigations in Geophysics, No. 10. Society of Exploration Geophysicists. https://doi.org/10.1190/1.9781560801580

Zabihi, N. E., & Siahkoohi, H. R. (2006). Single frequency seismic attribute based on short-time Fourier transform, continuous wavelet transform, and S transform. *6th International Conference & Exposition on Petroleum Geophysics*, Kolkata, 662–666.