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Spectral-derived Attributes Analysis and Interpretation using Enhanced Spectral Decomposition Method - A Case Study of Penobscot and Stratton Fields

Maryam Mahsal Khan [1*] , Ferhana Masood[2]
[1] Department of Computer Science, CECOS University of IT and Emerging Sciences, Peshawar, Pakistan
[2] Department of Earth Sciences, Quaid-i-Azam University, Islamabad, Pakistan

*Corresponding Author: maryam.khan@cecos.edu.pk

Abstract

Spectral analysis of data, whether seismic or well-log, provides another dimension of analysis and interpretation. These integrations are expected to lead to more accurate and detailed characterization of subsurface formations, which will have important implications for the oil and gas industry and other fields that rely on geophysical data. Spectral decomposition has been used to extract and determine lithological boundaries, reservoirs, etc. However, the methods fail at providing both high time and frequency resolution. The window length and the fact that the actual signal does not drop to zero outside of the artificially constrained time frame determine the resolution of the technique. Additionally, these techniques typically do not make use of the crucial thickness data that is computed in the Fourier phase spectrum. Spectral decomposition is a fundamental mathematical tool that is widely used in machine learning and other fields of data science and engineering, and forms the basis of many machine learning algorithms and techniques. We propose to use an improved spectral decomposition technique known as Continuous Amplitude Phase Spectrum (CAPS), which offers high frequency resolution as well as high time/depth resolution of the amplitude and phase spectra. The study used publicly available seismic datasets from two fields, i.e, Stratton and Penobscot, and two wells from the Penobscot field, L-30 and B-41, with gamma-ray, sonic, density, and neutron porosity logs. The areas of interest highlighted by the features derived from CAPS decomposition of the seismic and well log data were found to be in good agreement with the reported findings.

Keywords: *Seismic interpretation, signal processing, spectral decomposition, machine learning*

I. INTRODUCTION

Spectral analysis of seismic and well log data is an important tool in the field of geophysics for identifying and characterizing subsurface formations of oil and gas reserves. Spectral analysis can be used to identify the frequency components in seismic and well log data and to extract information about the physical properties of the subsurface formations. For both qualitative and quantitative interpretation of bed thickness, lithology, discontinuities, channels, pore fill, and structure, spectral properties resulting from the decomposition of seismic and well logs into frequency bands are useful [20][21][22]. Spectrally derived attributes provide another dimension of interpreting the reservoirs. Drilling dry holes can be decreased by including spectral characteristics into the decision-making process [25]. Recent research in this field has focused on several key areas, including (1) improved methods for processing and interpreting seismic and well log data, (2) the integration of multiple data sources for more accurate results, and (3) the development of new algorithms and tools for spectral analysis.

In seismic spectral analysis, [6] introduced a method based on a time-frequency analysis technique called the S-transform. The S-transform is a powerful tool for identifying non-stationary signals in seismic data, and the study found that it provided more accurate and detailed results than traditional Fourier-based methods. The research study by [12] demonstrated the effectiveness of combining multiple seismic data sources for spectral analysis. The study used data from both surface seismic surveys and borehole seismic measurements and found that combining these data sources allowed for more detailed and accurate characterization of subsurface structures [4] introduced a machine learning approach to spectral analysis of seismic data. The researchers used a deep learning algorithm to analyze seismic data and predict subsurface properties such as lithology and porosity. The method was found to perform well in identifying subtle subsurface features that are difficult to detect using traditional spectral analysis techniques.

In Well-log spectral analysis, [17] presented a novel method for spectral analysis of well log data based on the discrete wavelet transform (DWT). The method was found to provide more accurate results than traditional Fourier-based methods, particularly in cases where the data is noisy or contains non-stationary signals. In a research study by [3], the group demonstrated the effectiveness of using multiple well log data sources for spectral analysis. The study used data from different types of well logs, including gamma ray, resistivity, and sonic logs, and found that combining these data sources improved the accuracy of the spectral analysis and allowed for more detailed characterization of subsurface formations. While in a recent study by [7] introduced a machine learning approach to spectral analysis of well log data. The researchers used a convolutional neural network (CNN) to analyze well log data and extract features related to subsurface formation properties. The CNN was found to perform well in identifying lithology and porosity variations in the subsurface, and the method has the potential to be applied to large-scale datasets.

Overall, several spectral decomposition techniques, Short-time Fourier Transform (STFT), S-Transform, Continuous Wavelet Transform (WT), Discrete Wavelet Transform, Matching Pursuit Decomposition, have been suggested and used in various branches of science and engineering over the past ten years, including seismic and well log signal analysis. In the context of seismic and well-log signal processing, these methods provide another dimension of analysis, frequency, by relating reservoir parameters to bright or dim amplitude anomalies. In a wide seismic spectrum, such abnormalities are frequently concealed among numerous frequencies. The spectral decomposition techniques STFT and WT aim to increase the time-frequency precision of the data. To identify reservoir fluids, litho-stratigraphic boundaries or discontinuities, and estimate reservoir in boreholes, these methods have also been used in wire-line logging. [16][13][18]. All of these techniques aim to increase the STFT's time-frequency precision restriction, which mainly focuses on adjusting the window length to regulate resolution.

The current research presents a case study, and the main contributions of which are as follows:

A. Using high-resolution time-frequency volumes

The main ingredient in reservoir properties identification and interpretation is the use of a high-resolution-based spectral transformation technique. Whereby, the resolution of such techniques is highly dependent on the length of the window, which inversely affects the frequency resolution of the data signal analysed. In this context, a novel spectral decomposition method has been introduced that provides both high time and high frequency resolution, known as

Continuous Amplitude Phase Spectrum (CAPS). The CAPS transform, proposed and patented by [11], has been used to generate high-resolution attributes for seismic interpretation and auto-steering trackers in three-dimensional seismic horizon surfaces [2]8][9][10][11]. In the current research study, high-resolution time-frequency volumes of two publicly available datasets [14][15] are generated using the CAPS transform. The dataset also came with four logs: Gamma-ray, density, sonic, and neutron porosity from two wells. For the mathematical formulation of how the amplitude and phase spectra are derived using the CAPS transform, readers are referred to the detailed research presented in [11]

B. Deriving spectral parameters from CAPS Transform

Spectral decomposition offers important insights into the subsurface geology and reservoir characteristics by deriving a number of attributes. Instantaneous frequency, frequency slice maps, spectral coherence, spectral curvature analysis, etc., are a few of the characteristics that are frequently mentioned in the literature. The current study will concentrate on three of the most common metrics that are successfully used to examine the subsurface properties of reservoirs. CAPS-based spectral parameters are computed and are found to correlate with already discovered reservoirs.

Apart from its applicability in Earth Sciences, spectral parameters have been successfully applied in a wide range of scientific fields [27][28][29]. In the medical field, these parameters offer insightful information regarding physiological processes and support the detection of anomalies or probable health problems. Detecting anomalies like epileptic seizures, sleep disorders, or mental disorders from EEG signals, detecting anomalies in heart rhythm from ECG signals, and identifying tissue composition via spectral analysis of MRI or spectroscopy are a few of the many applications where spectral analysis has been successfully used.

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II. METHODOLOGY

A. Seismic Pre-processing

A spectral decomposition method, Continuous Amplitude and Phase Spectra, CAPS [1], is used to generate high-resolution time and frequency spectra across both amplitude and phase. This technique creates multiple amplitude and phase volumes from a single seismic volume, just like other spectral decomposition methods. Its resolution is higher, and it is not constrained to the preset time frame centered on the interpreted horizon. Instead, the seismic trace as a whole is used to calculate it. As a result, the user is able to investigate seismic volume anomalies without having to decide on a time frame beforehand through interpretation. We integrate the spectral data over automatically chosen bands, particularly with a high signal-to-noise ratio, to emphasize desired reservoir features because it takes time to visualize and understand each frequency volume. This method combines numerous frequency volumes into a single attribute, referred to as spectral parameters, that is then mapped onto a colour bar. As a result, strange colour patches in the volume or on a horizon can be found swiftly and with ease. The spectral parameters investigated in this research study include: spectrum variance, amplitude gradients, and peak frequency, as described ahead. We then combine these characteristics to create mega attributes for reservoir parameter sensing.

B. Well Log Pre-processing

The borehole logs that include gamma ray, neutron porosity, sonic, and density are first detrended to remove the DC component. The transients are then smoothed by using an n-point moving average filter. The well logs are then transformed into the time-frequency domain using CAPS. Spectral parameters, namely spectrum variance, amplitude gradients, and peak frequency, are then derived from the computed CAPS profile.

C. Spectral Parameters

Several attributes can be derived from spectral decomposition, providing critical insights into the subsurface geology and reservoir characteristics. Some of the common attributes in literature include instantaneous frequency, frequency slice maps, spectral coherence, spectral curvature analysis, etc. Three of the most popular metrics that are successfully employed to analyse the subsurface characteristics of reservoirs will be the focus of the current study.

Spectral Variance: It is the variance in the frequency distribution of the amplitude and phase spectra at each time/depth measurement in the seismic/borehole log measurements. For a homogeneous geological structure, the spectral variance is minimum. With the inclusion of structural faults or the presence of oil & gas reservoirs, the variance in the spectrum across the breadth and depth of the seismic or well log spectrum increases. Incorporating these spectrally variant zones could further improve reservoir interpretation and characterization.

Instantaneous Frequency or Peak Frequency: It is the dominant frequency recorded during each time/depth measurement. It provides information about the variation in geological features, anomalies, and stratigraphy. Visualization of a seismic volume across this parameter is referred to as a spectral colormap. According to [12], sandstone segments with a high peak frequency are thicker than those with a low peak frequency. The high and low frequency value changes with the geological features and stratigraphy.

Amplitude Gradient: it is the slope of the amplitude at peak frequency with the amplitude at the highest cut-off frequency in the spectrum. According to [5], the slope represents the strata absorption rate. The parameter measures the change of frequency at hydrocarbon zones.

III. CASE STUDIES

The methodology is applied across two publicly available datasets [14][15]. Seismic data of the Stratton and Penobscot fields, while borehole log measurements from the Penobscot field are analysed in the current research study.

A. Field Details

Seismic Data: The seismic data of the **Stratton field**, US, consists of two significant formations, namely Frio and Vicksburg. A visual map of the field is shown in Figure 1. These formations are known to generate significant gas reserves. Geologically, the lower Frio and Vicksburg formations are split by several normal faults, while the upper and middle Frio formations are structurally smooth and undisturbed. The MidFrio Formation contains a horizon surface named C38. The change in spectral parameters is investigated in these formations to understand their correlation with varying structural and reservoir characteristics of the formation. The geological core of the site can be found in [19]. CAPS is computed for the Stratton field, where the spectrally derived parameters are measured with a band-pass frequency of [18,32] Hz.

Penobscot: It is located on Canada's Scotian coast. The visual map of the field is taken from Baroni, Lais et al. (2019) and shown in Figure 2(a). In the Jurassic Abenaki Formation's Misiane and Baccaro members, two wells, L-30 and B-41, were dug. The seismic 3D image with the two wells L-30 and B-41 is shown in Figure 2(b). Based on report findings, L-30 had 16m of potential pay sands, whereas B-41 had no discernible evidence of hydrocarbon deposits [15]. The dGB Earth Sciences' interpreted horizons are used to reflect the variation in spectral parameters computed in the current study. The geological core of the site can be found in [15]. The three-dimensional seismic data is converted into a time-frequency domain using CAPS. The spectral parameters previously stated are derived from the frequency volumes. A band-pass frequency of [14, 34] Hz was employed. This is done in order to get high resolution levels while also reducing noise in the process.

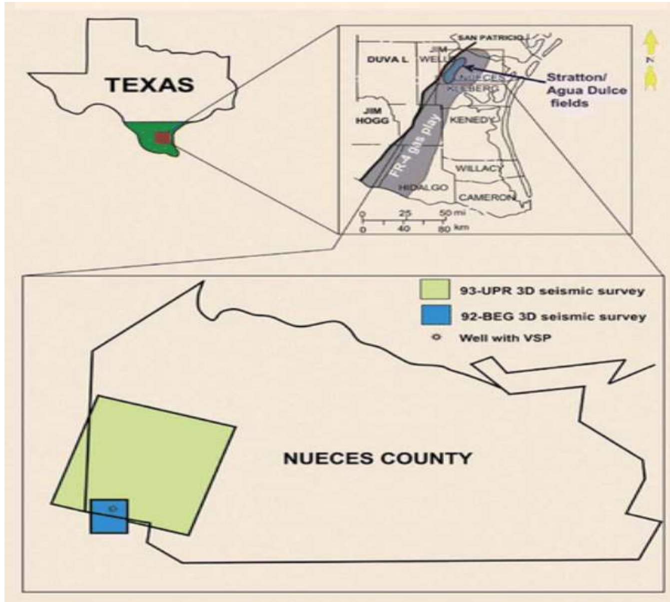


Figure 1: Location of the Seismic 3D survey in Texas, US. Image is taken from [19]

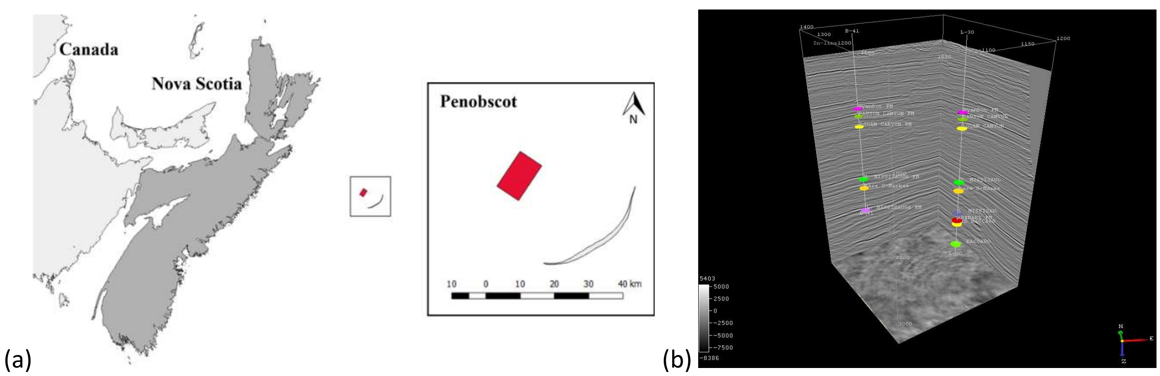


Figure 2: (a) Visual Map of Penobscot Field, Nova scotia. Taken from Baroni, Lais et al. (2019); (b) 3D seismic image with two wells L-30 and B-41.

B. Seismic CAPS Analysis

Stratton Field: The variation of the derived spectral parameters from CAPS is observed on the horizon surface C38, shown in Figure 3(a,b,c). Strong anomalies are depicted in Figure 3(a), where negative amplitude-vs-frequency gradients signify frequency attenuation, which [4] claim indicates the presence of oil/gas reserves. Figure 3(b) shows the amplitude variance in the defined band-pass spectrum, with the highest variance in the region indicated by the arrow. The characteristics of the stratigraphic interface have changed in this region. High peak frequency is shown in Figure 3(c), which [12] claims is related to thick sandstone intervals

Penobscot Field: The Base O'Marker, which is located between the Upper and Lower Mississauga Formations, correlates to Horizon H1, which is used as a reference to analyze change in spectral parameters. H1 is above the Sand#1 Formation. The Sand #1 Formation has a fluid yield of 3400cc of oil and 1cf of gas, with a porosity of 0.22% and a water saturation of 0.38%. [14]. The spectral characteristics of amplitude gradient, spectral variance, and peak frequency across H1 are shown in Figure 3(d,e,f). Figure 3(d) encompasses the majority of the horizon surface and displays bright spots near the L-30 and B-41 wells' surrounding areas. Faults and the existence of hydrocarbon reserves are the causes of the anomalous behaviour. The amplitude's spectral variation at the designated pass-band frequency is shown in Figure 3(e). We find more variation in the vicinity of B-41. This shows a shift in the reservoir characteristics of the horizon close to dry well B41. Medium and high peak frequencies are depicted in regions with unusual activity in Figure 3(f). When linked with peak frequency, the high spectral variance seen in Figure 3(e) reveals that the anomaly correlates with thick sandstone intervals. Therefore, by observing the change in frequency of the seismic signals, reservoir thickness can be inferred.

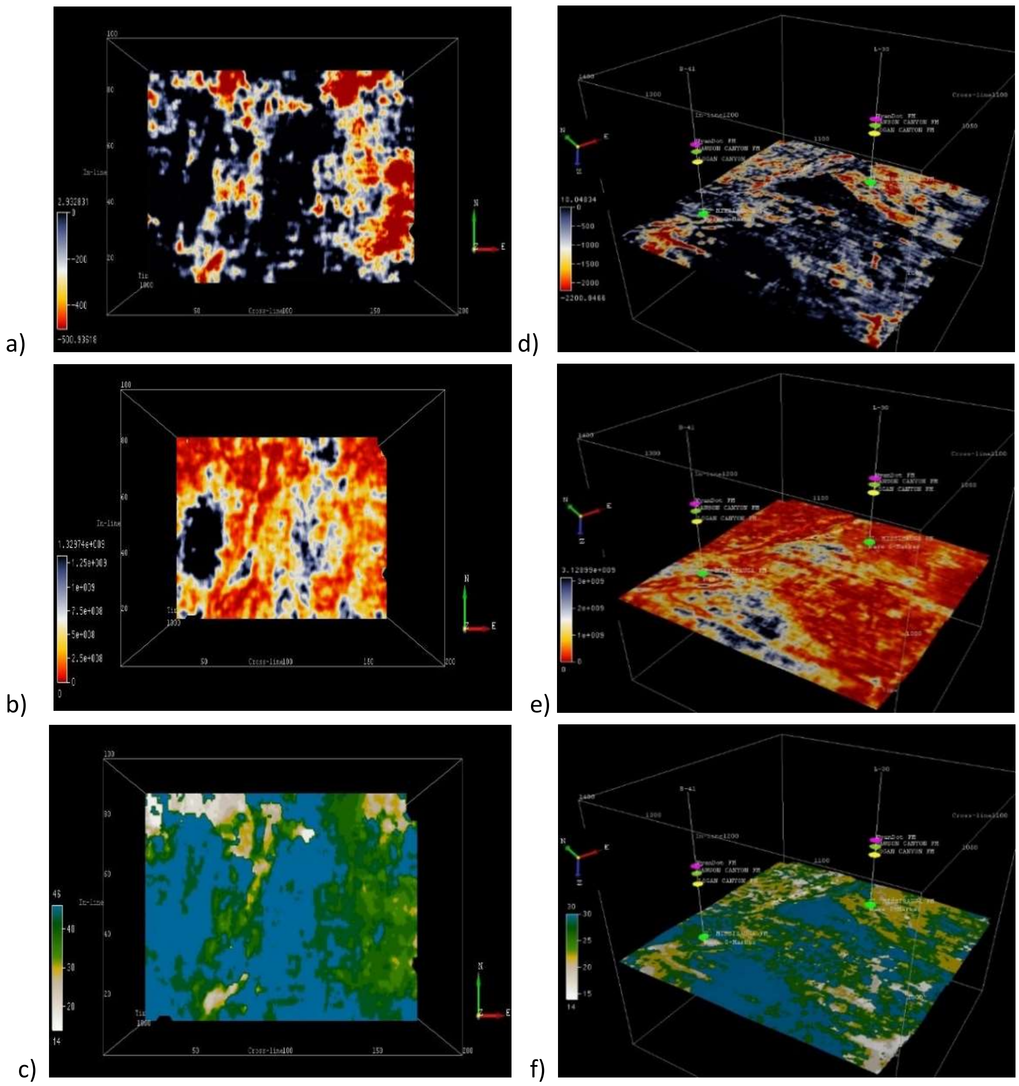
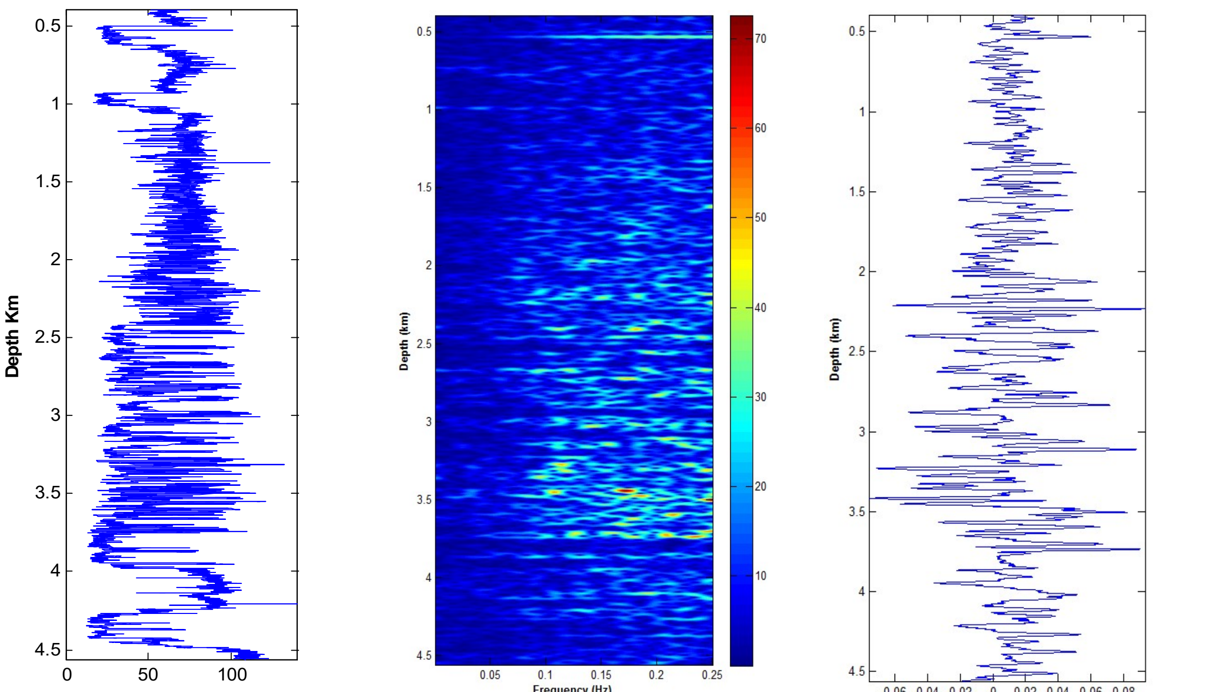


Figure 3: Spectral parameters analysis from the Stratton and Penobscot field. High-resolution based CAPS volumes are generated from the seismic data, where derived attributes (a,d), Amplitude Gradient (b.e), Spectral Variance (c,f), Peak Frequency, from the magnitude spectrum, are computed for Stratton(a-c) and Penobscot(d-f), respectively

C. Well log analysis of Penobscot Field

L30 Well: Gamma ray log of the L-30 well from the Penobscot field is shown in Figure 4(a), with hydrocarbon-bearing sandstone intervals clearly indicated [15]. The gamma-ray log is first pre-processed, as mentioned in the methodology. It is then decomposed into amplitude and phase spectrum using CAPS. The CAPS transform's amplitude spectrum (Figure 4b) shows regions with high frequency content. These areas correlate to the sandstone intervals, but the tight limestone carbonates are actually represented by an area of about 3.5 km. Each depth sample's amplitude spectrum gradient is calculated in the band-pass frequency range of [0.1, 0.25] Hz. The attenuation of frequency at each level is captured by the amplitude gradient. Figure 4(c) shows that four peaks are created, each of which corresponds to a sandstone zone. This indicates that the CAPS spectrum and its spectral-derived attributes have the potential to identify and emphasize zones of interest, which will facilitate interpretation.

The CAPS amplitude spectral graphs for L-30 well's sonic, density, and neutron porosity log are shown in Figure 5. We can see bright spots slightly above 2.4 km, which actually correlate to porous sandstone intervals, because sonic logs assess the porosity of structures. Similar to density, porosity is measured by density, and we can see that the reservoir's characteristics shift between 2.5 and 4 kilometres, with tight limestone carbonates found beyond 3 kilometres. The hydrogen concentration of lithologies, which may be related to water or hydrocarbons, is measured by neutron porosity. In structures located 2-3 km away, a noticeable shift in hydrogen content can be seen. While 9700 cc of water was discovered at Sand # 5 at a depth of 2.7Km, hydrocarbon reserves were located from Sand #1 to Sand #4, or 2.4Km to 2.6Km [15].



a) b) c)

Figure 4: L-30 bore-hole in Penobscot Field (a) Gamma-ray Log (b) Magnitude spectrum of gamma-ray log via CAPS decomposition (c) Amplitude gradient of the magnitude spectrum in (b) at band-pass frequency of [0.1,0.25] Hz

B41 Well: Figure 5 shows the CAPS amplitude spectrum for a detrended and filtered B-41 well record. We can see that bright spots take up the majority of the frequency range, ruling out hydrocarbon anomalies as the cause. Additionally, if we compare the colour bars for amplitude, we see that L-30 has covered a higher amplitude range than B41. In L-30, the highest amplitude of the sonic log reached 80, whereas in B-41, it is 30. This shows the B-41 well's permeability has significantly decreased.

The crossplot of the amplitude gradient of the well logs from both wells at all depths is shown in Figure 6. When compared to the B-41, the L-30 exhibits significant variance that is easy to see. This shows that large amplitude gradients are measured for carbonates with hydrocarbon reserves.

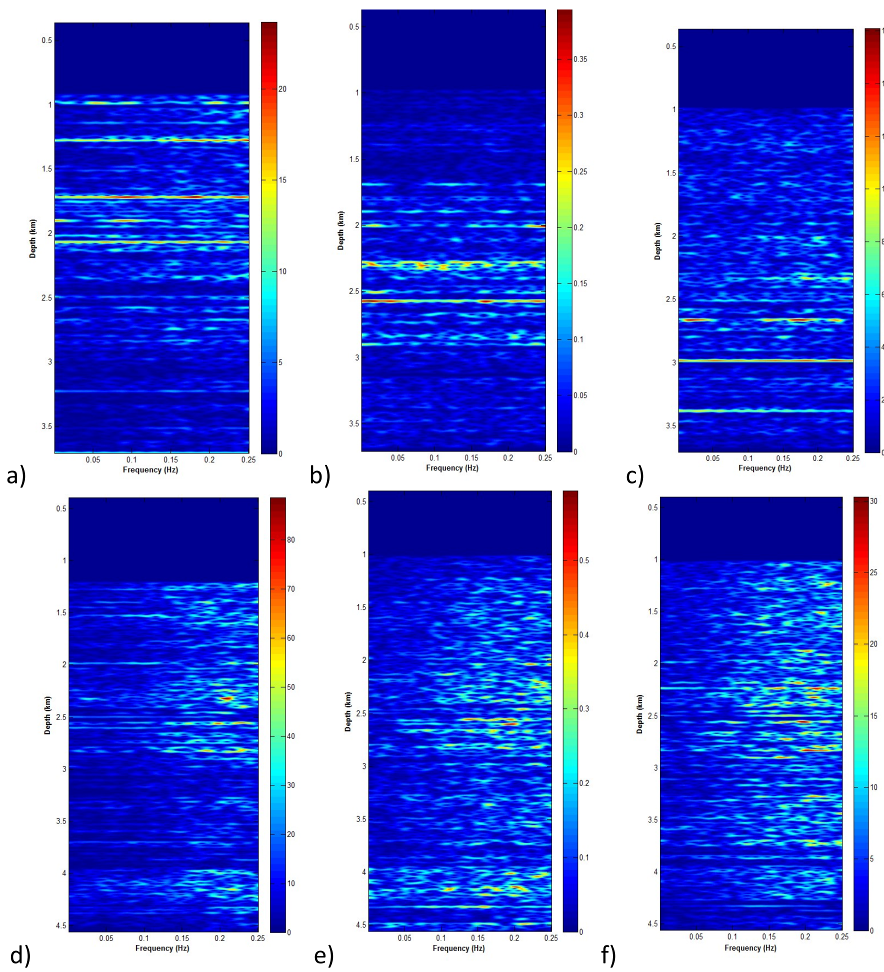


Figure 5: Time-frequency decomposition using CAPS on Penobscot Field's Well L-30 (a-c) and Well B-41 (d-f). The magnitude spectrum for (b,d) Sonic (c,e) Density (d,f) Neutron porosity logs are displayed herewith for each well.

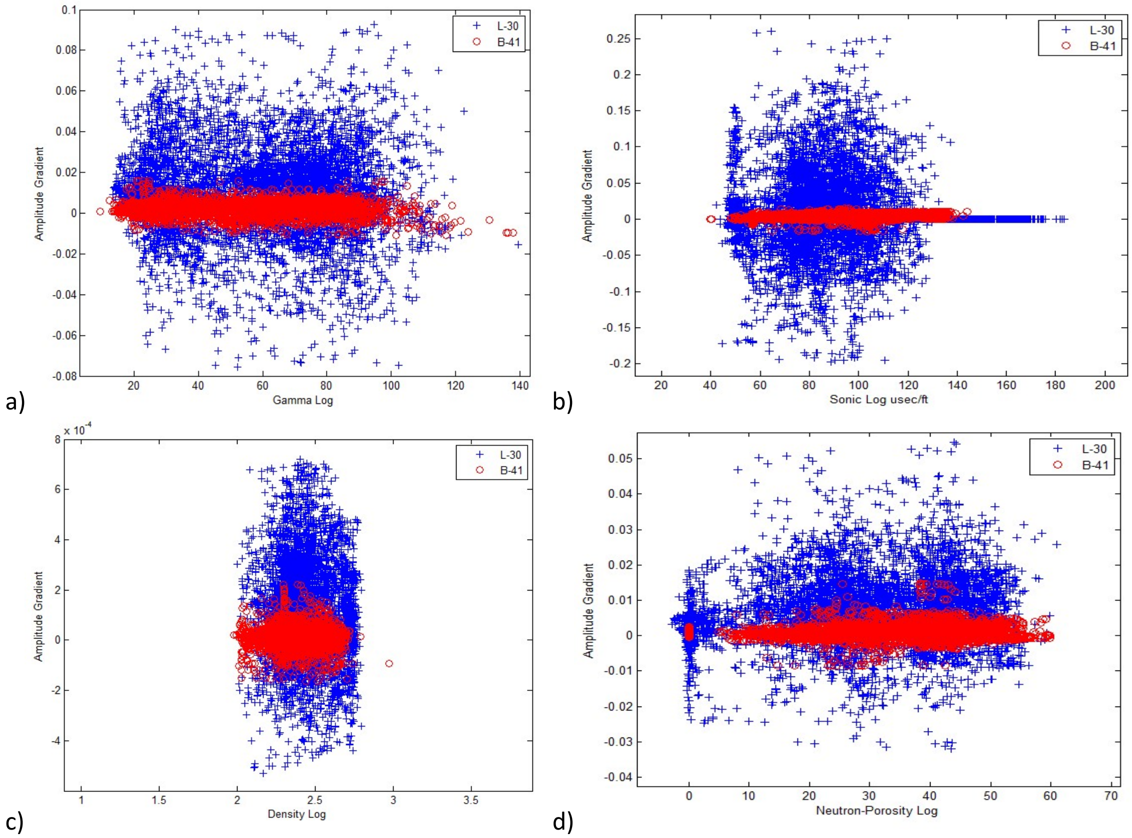


Figure 6: Cross plot of amplitude gradients obtained for Well L-30 and B-41 of Penobscot Field of (a) Gamma Log (b) Sonic (c) Density and (d) neutron porosity measurements.

IV. CONCLUSION

A spectral decomposition method, Continuous Amplitude Phase Spectrum, is employed on a public dataset with three-dimensional seismic data and borehole logs. The method generates high-resolution frequency volumes with high SNR, which are produced using the ideal windowing parameters.

For interpreted horizons in the Penobscot and Stratton fields, spectral parameters such as amplitude gradient, spectral variance, and peak frequency were recorded. Based on our analysis, we draw the conclusion that in both seismic surveys, a thicker sandstone interval with hydrocarbon reserves correlates to a high amplitude gradient, low frequency amplitude variance, and high peak frequency. Using spectral parameters provides further insight into the data analysed and helps in reducing the interpretation cycle time.

From the Penobscot field, gamma ray, sonic, density, and neutron porosity logs were analyzed. The spectral analysis of logs revealed hidden structures and characteristics of the earth's strata. The findings from the proposed process highlighted areas of interest, such as hydrocarbon zones, which were consistent with the results previously reported. As future work, the method needs to be tried out on additional wells with known petro-physical analyses. Other traits that are drawn from spectral data must also be measured and used to calculate the reservoir properties of the formation.

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