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Application of Frequency Attenuation Hydrocarbon Detection Method in Ultra-Deep Carbonate Reservoir Exploration

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Abstract

Based on the biphasic medium theory, this paper proposes a hydrocarbon detection method that integrates multi-scale frequency-varying characteristics, enhancing the hydrocarbon response features in seismic data by optimizing sensitive attributes. Model simulations and actual data validation demonstrate significant differences in low-frequency energy attenuation gradients between oil-bearing and water-bearing reservoirs: oil layers exhibit enhanced high-frequency components, while water layers are dominated by low-frequency energy. In practical applications, this method effectively delineates the oil-water boundaries of structural hydrocarbon reservoirs in the C9 block of the Qaidam Basin by extracting frequency attenuation gradient attributes. The planar prediction results show high consistency with drilling interpretations, revealing the oil-bearing potential of reservoirs in structural slope areas. Compared to traditional pre-stack inversion techniques, this method significantly improves the accuracy of oil-water differentiation identification, providing new technical support for ultra-deep carbonate reservoir exploration.

Keywords

Qaidam Basin, Carbonate Reservoirs, Biphasic Medium Theory, Hydrocarbon Detection

1. Introduction

With the rapid development of high-precision seismic technology, the frequency bandwidth of seismic data has significantly expanded, enriching both high- and low-frequency information. Traditional pre-stack inversion techniques for identifying lithology, physical properties, and hydrocarbon-bearing characteristics are heavily influenced by gather quality (Huang et al., 2025, Zhang et al., 2024), long constrained by factors such as migration angles and the amplitude, phase, and frequency consistency of near, mid, and far stack data. In recent years, the importance of low-frequency components in hydrocarbon detection has become increasingly prominent (Zhang et al., 2021, Liu et al., 2019). Scholars have proposed methods such as low-frequency absorption attenuation gradient detection based on improved generalized S-transform (Li et al., 2019), wavelet decomposition techniques (Zhang et al., 2021, Liu et al., 2019), and empirical mode decomposition for low-frequency energy variation rates (Qin et al., 2017, Chen et al., 2009), effectively enhancing the identification capability of concealed gas reservoirs. However, conventional time-frequency analysis methods suffer from insufficient resolution and energy dispersion, making it difficult to accurately extract hydrocarbon anomaly features embedded in broadband responses.

This paper proposes a hydrocarbon detection method that integrates multi-scale frequency-varying characteristics by optimizing sensitive attributes based on biphasic medium theory to identify oil-water differentiation. Compared to traditional methods that delineate oil layer thickness based on drilled wells, this method significantly improves the accuracy of identifying oil-water boundaries in structural hydrocarbon reservoirs by enhancing the hydrocarbon response features in seismic data, providing new technical support for ultra-deep carbonate reservoir exploration.

2. Time-Frequency Analysis Methods

2.1. Method Principles

Wavelet Transform, WT

The concept of wavelet transform was first proposed by Morlet et al. in the late 1970s to early 1980s and later developed into a systematic theoretical framework by Daubechies et al. (Chen et al., 2009, Wei & Wang, 2012). Wavelet transform performs multi-scale analysis of signals by scaling and translating a mother wavelet basis function. Its essence lies in utilizing the localization properties of wavelets to provide joint time-frequency analysis capabilities. It is suitable for non-stationary signal analysis, particularly in transient feature detection, signal denoising, and image compression. The advantages of this method include: multi-resolution analysis capability, capturing both high-frequency transient features and low-frequency trends; strong time-frequency localization, avoiding the global limitations of Fourier transform; and high computational efficiency, making it suitable for real-time processing. The continuous wavelet transform is defined as:

$$W(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} f(t)\psi^{*}\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

Here, a is the scale factor controlling wavelet dilation, bis the translation parameter controlling time localization, $\psi(t)$ is the mother wavelet basis function, and $W(a,b)$ is the wavelet coefficient.

Generalized S-transform, GST

The S-transform was initially proposed by R.G. Stockwell in 1996 as an improvement over traditional short-time Fourier transform, optimizing time-frequency resolution by adjusting window width (Zhang, 2011, Xiong et al., 2011). The generalized S-transform extends the traditional S-transform by dynamically adjusting the width of the Gaussian window to achieve adaptive optimization of time-frequency resolution. The variability of the time-frequency window balances the representation of high-frequency details and low-frequency trends, making it suitable for signal processing scenarios requiring high time resolution for high-frequency components while retaining frequency details of low-frequency components.

The generalized S-transform is defined as:

$$S(\tau, f) = \int_{-\infty}^{\infty} f(t)\omega(\tau - t, f)\mathrm{e}^{-i2\pi ft}\mathrm{d}t$$

Here, the window function $\omega(\tau - t, f) = \frac{|f|}{\sqrt{2\pi}}\mathrm{e}^{-\frac{f^2(\tau-t)^2}{2}}$ adjusts the window width through frequency f, achieving time-frequency adaptivity. This method has a simple mathematical form and is easy to implement, but its results are less stable due to manual tuning of parameters such as Gaussian width and are more susceptible to data signal-to-noise ratio, with weaker anti-interference capability.

Matching Pursuit, MP

The concept of matching pursuit was first proposed by Stéphane Mallat and Zhang in 1993, representing an important method in the field of sparse representation (Yue et al., 2016, Tian et al., 2015). Its core idea is to decompose a signal into a linear combination of atoms (from a predefined redundant dictionary), with each atom matching the current residual part of the signal's time-frequency characteristics as closely as possible. This algorithm captures local time-frequency features of signals, making it particularly suitable for nonlinear and non-stationary signal analysis.

$$f(t) = \sum_{k=1}^{K} a_k \psi_{\gamma k}(t)$$

Here, $\psi_{\gamma k}(t)$ is the k-th atom selected from the redundant dictionary, is the corresponding coefficient, and represents the atom parameters (e.g., frequency, scale).

n practical applications, this method has high computational complexity, with an iterative process that is time-consuming. The choice of the atom library directly affects the decomposition results, potentially leading to local optima or mathematical non-convergence.

Biphasic Medium Theory

Biphasic medium theory was proposed by Biot in 1956, with its core focus on describing the wave behavior of composite media composed of a porous solid skeleton (solid phase) and pore fluids (fluid phase) (Liu et al., 2010, Li et al., 2017).

When elastic waves propagate in biphasic media, interactions between the solid and fluid phases due to relative displacement excite a second type of longitudinal wave (slow P-wave). This theory quantifies the dynamic response of biphasic systems through wave equations, expressed in vector form as:

$$N\nabla^2 u + \nabla\left[(A+N)\theta + Q\varepsilon\right] = \frac{\partial^2}{\partial t^2}(\rho_{11}u + \rho_{12}U) + b\frac{\partial}{\partial t}(u-U)$$

$$\nabla\left[Q\theta + R\varepsilon\right] = \frac{\partial^2}{\partial t^2}(\rho_{12}u + \rho_{22}U) - b\frac{\partial}{\partial t}(u-U)$$

Here, A and N are elastic parameters of the solid phase, corresponding to Lamé constants in single-phase media; Q and R characterize solid-fluid coupling effects and fluid compressibility, respectively; $\rho 11$, $\rho 22$ and $\rho 12$ represent the equivalent mass densities of the solid phase, fluid phase, and their coupling term, respectively; θ and ϵ are volumetric strain parameters; u and U are displacement vectors of the solid and fluid phases, respectively; and b is the dissipation coefficient, expressed as $b = \frac{\mu\varphi^2}{k}$ and directly related to fluid viscosity, directly related to fluid viscosity μ, porosity φ, and permeability k.

Actual seismic signals can be regarded as superimposed responses of the first P-wave and slow P-wave, with dynamic characteristics significantly different from single-phase media. Theoretical model simulations show that seismic waves in biphasic media exhibit a spectrum characterized by "enhanced low-frequency energy and attenuated high-frequency energy," a phenomenon closely related to the viscous dissipation of pore fluids and solid-fluid coupling effects, providing a physical basis for identifying hydrocarbon reservoirs.

2.2. Algorithm Description

Any signal can be decomposed into several Intrinsic Mode Functions (IMFs). A signal can contain multiple IMFs. If IMFs overlap, they form a composite signal. Using time-frequency decomposition methods, the seismic signal $x(t)$ is decomposed into the sum of all IMF components and a residual, which can be expressed as:

$$x(t) = C_1(t) + C_2(t) + \cdots + C_n(t) + r_n(t)$$

where: $C_i(t)$ (i = $1, \ldots, n$) represents the i-th IMF component; $r_n(t)$ is the residual. The number of IMF components is related to the seismic signal and the given termination standard deviation limit.

Hilbert spectral analysis is performed on each IMF component to obtain instantaneous frequency, amplitude, and phase. After a series of transformations, the original seismic signal $x(t)$ can also be expressed as:

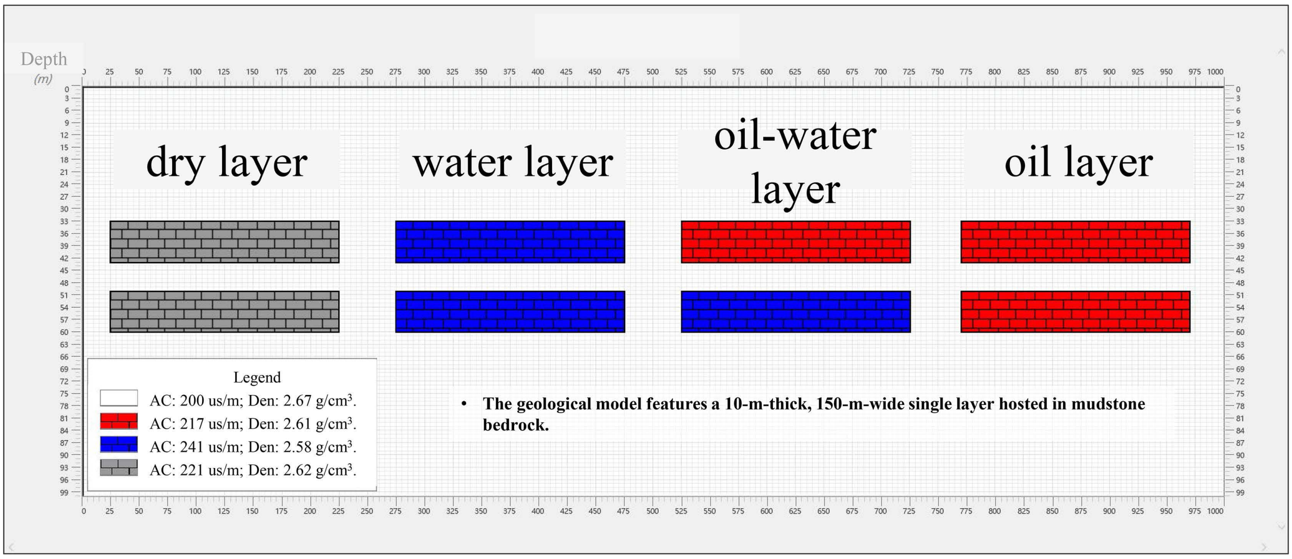
$$\begin{aligned} x(t) &= C_1(t) + C_2(t) + \cdots + C_n(t) + r_n(t) \\ &= \sum_{i=1}^{n} \mathrm{Re}\left[a_i(t)\mathrm{e}^{j\varphi_i(t)}\right] + r_n(t) \end{aligned}$$

where: $a_i(t)$ is the instantaneous amplitude; $\varphi_i(t)$ is the instantaneous phase.

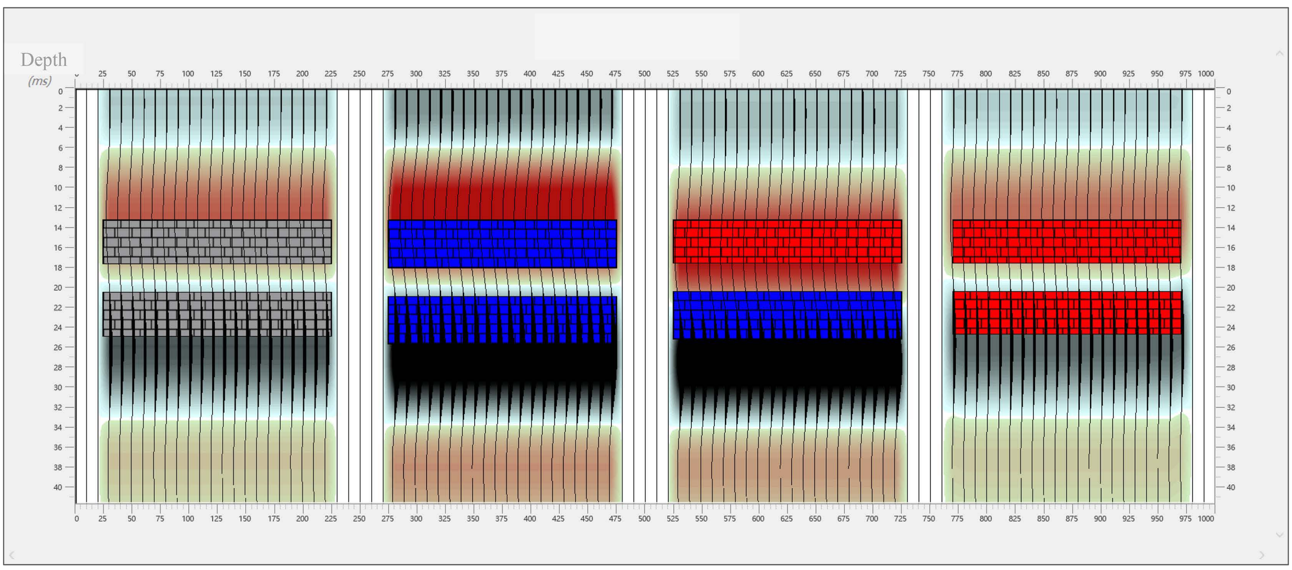
In the generated time-frequency spectrum, the spectrum is extracted trace by trace along time points, and its low-frequency slope is calculated, thereby obtaining the low-frequency energy variation rate.

2.3. Model Simulation

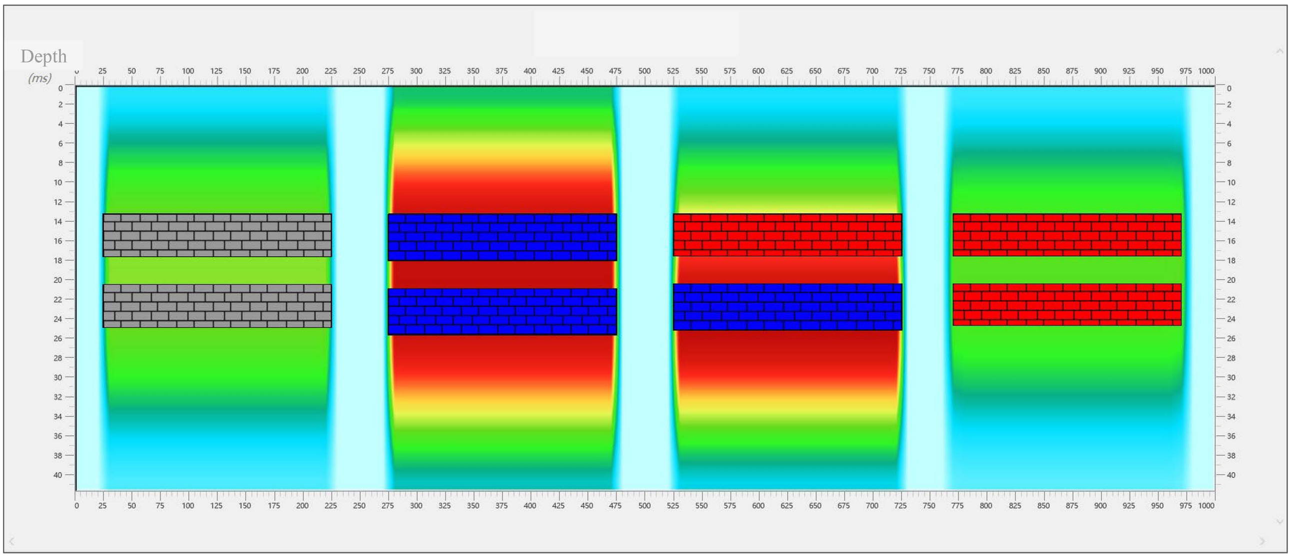
Based on logging data from actual drilling wells in the western depression of the Qaidam Basin, an oil-bearing model was established. The geological model designed two reservoir layers in a mudstone background, assuming four common hydrocarbon distribution scenarios: both layers as dry layers, both as water layers, upper oil and lower water, and both as oil layers (**Figure 1(a)**). Parameters such as velocity, density, and thickness in the model were primarily derived from statistical logging data. The geological model was converted into seismic data with a



(a)



(b)



(c)

Figure 1. Simulation model: (a) Geological model, (b) Seismic profile of the simulation model, (c) Frequency profile of the simulation model.

sampling rate of 1 ms, and the wavelet frequency was set to 25 Hz based on the dominant frequency of 3D data in the area, as shown in **Figure 1(b)**. Simulation analysis indicates that seismic event strength varies significantly with fluid properties, with amplitude changes following the order: water layer > oil-water layer > oil layer ≥ dry layer. Fine hydrocarbon detection based on this seismic data reveals strong frequency differences between oil-bearing and water-bearing reservoirs, demonstrating that low-frequency energy variation rates aid in characterizing oil-bearing reservoirs (**Figure 1(c)**).

2.4. Data Validation

Three well-crossing seismic profiles (C10, C12, and C3-5) were subjected to spectral decomposition, with energy distribution in the time-frequency domain delineated at steps of approximately 9 Hz. Well C10 was interpreted as primarily oil-bearing, well C12 as primarily water-bearing, and well C3-5 as oil-bearing in the upper section and water-bearing in the lower section, corresponding to one of the scenarios in the geological model.

Time-frequency profiles show that the dominant frequency of well C10 is concentrated at 24 - 43 Hz (**Figure 2**), well C12 at 14 - 33 Hz (**Figure 3**), and well C3-5's water-bearing section at 14 - 33 Hz and oil-bearing section at 24 - 43 Hz (**Figure 4**). Validation results indicate that seismic wave frequency properties primarily depend on rock skeleton, porosity, and pore fluid properties. When formations contain hydrocarbons, they exhibit enhanced high-frequency components; when they contain water, they show enhanced low-frequency components. This characteristic can be utilized to predict hydrocarbon-bearing properties.

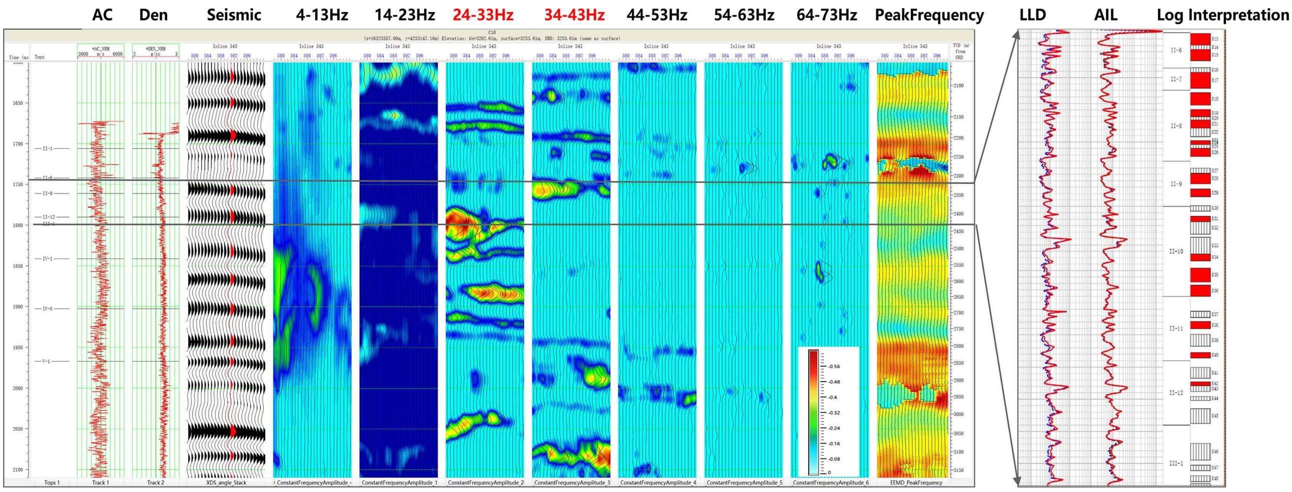


Figure 2. Time-frequency profile of well C10.

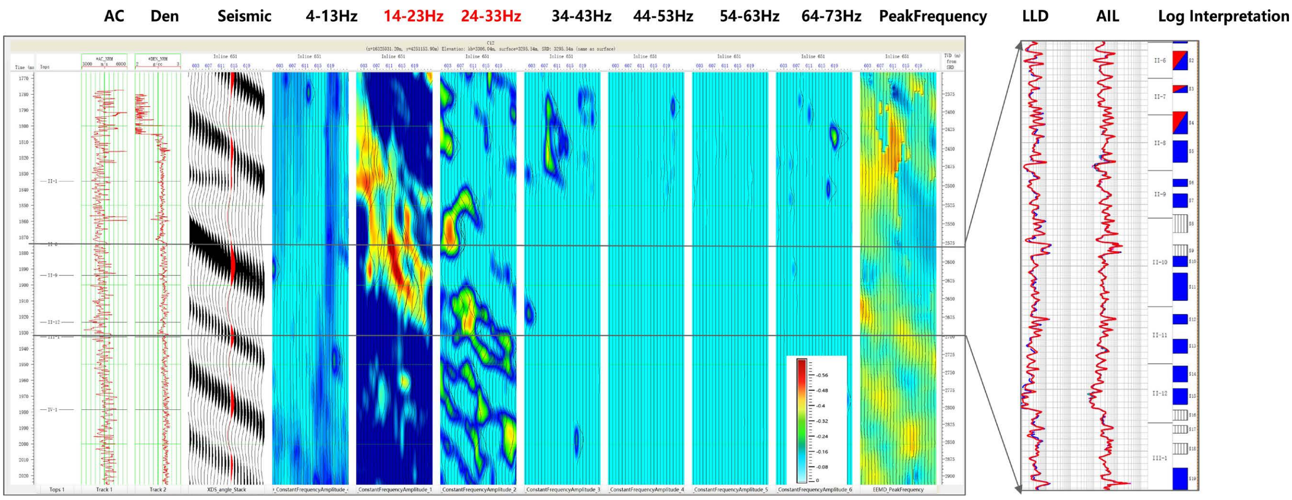


Figure 3. Time-frequency profile of well C12.

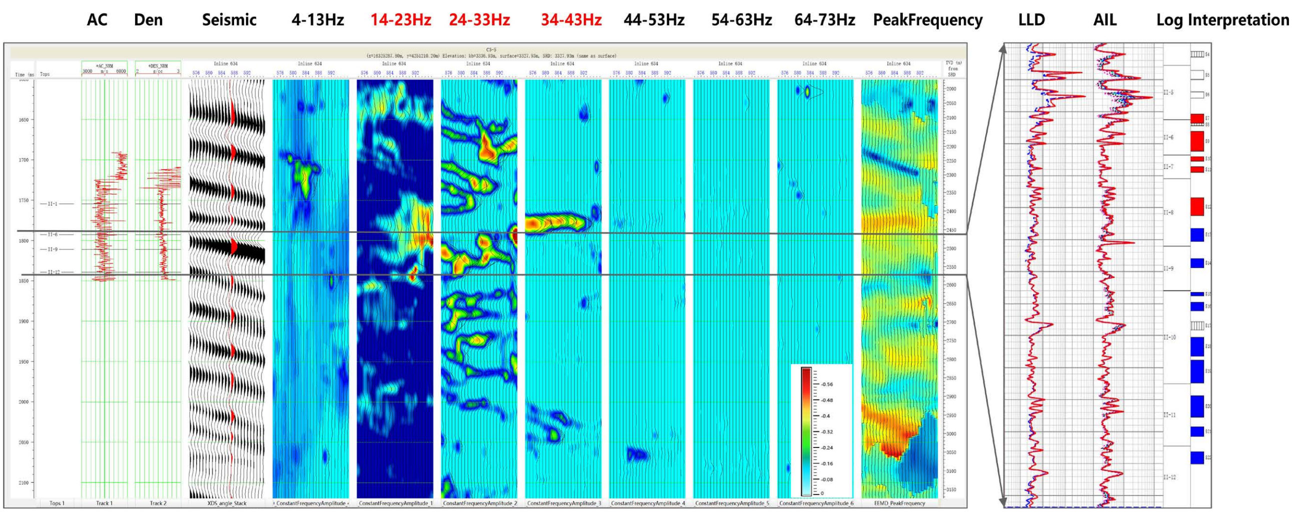


Figure 4. Time-frequency profile of well C3-5.

3. Reservoir Geological and Seismic Characteristics

3.1. Reservoir Geological Characteristics

The C9 block of the Ganchaigou Oilfield is located in the northern part of the western Qaidam Basin in Qinghai Province, exhibiting a faulted anticline structure overall. The target layer, E32, developed a fan delta-lacustrine sedimentary system from the piedmont to the basin. Vertically, it shows a regressive sedimentary trend: the lower section consists of semi-deep to shallow lake deposits, gradually transitioning to saline lake deposits upward. The oil-bearing reservoir II group primarily features dolomitic flat and lime-dolomitic flat as favorable facies, with dolomitic flat mainly developed in the II-6 and II-10 intervals and lime-dolomitic flat dominating other intervals. The dominant microfacies of the II group are dolomitic flat, lime-dolomitic flat, and muddy dolomitic flat, accounting for over 50% of the cumulative thickness. Previous studies analyzed oil-water interfaces based on well-test data from nearly 20 wells in the area, but understanding of oil-water distribution in inter-well and low-well-control regions remains limited.

3.2. Reservoir Seismic Characteristics

The study area is covered by pre-stack time-migrated 3D seismic data, with the maximum cutoff angle for the target layer in CRP gathers being less than 27 degrees, resulting in a narrow usable angle range. Additionally, the resolution of far-stack data is slightly lower than that of near- and mid-stack data, and lateral amplitude energy differences exist among near, mid, and far traces. Furthermore, the II6-12 oil layer group features multiple thin reservoirs vertically, with seismic resolution insufficient to identify individual oil layers. These factors contribute to significant ambiguity in conventional lithology-physical property-hydrocarbon prediction methods.

3.3. Practical Application

Using biphasic medium theory, the frequency attenuation gradient attribute was extracted to study the frequency variation characteristics along wells, as shown in **Figure 5**. The results indicate that oil-bearing reservoirs exhibit larger frequency attenuation gradients, represented by strong warm-colored amplitude anomalies, while water-bearing or oil-water reservoirs appear as cool-colored amplitude anomalies. The profile characteristics align with actual drilling results, demonstrating that this method can qualitatively identify fluid differentiation in reservoirs.

The planar variation of the frequency attenuation gradient attribute along the II6-II9 interval is shown in **Figure 6**. Based on low-frequency signal theory and simulation results, high-quality reservoirs correspond to moderate-to-strong amplitude low-frequency energy variation rates, where strong low-frequency energy variation rates correlate with industrial oil flow, while weak anomalies correspond to non-productive wells. Compared to the oil layer thickness map (**Figure 7**), the

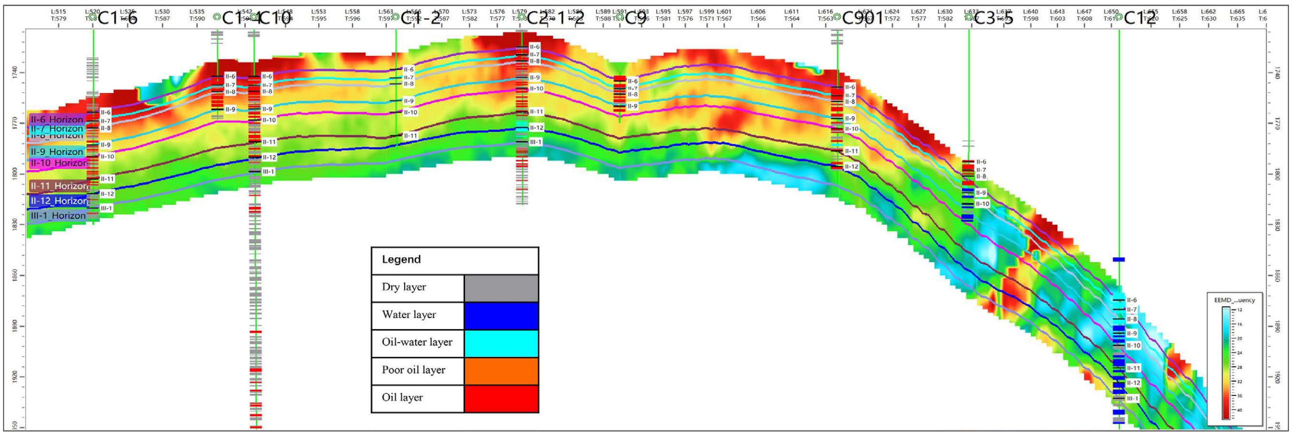


Figure 5. Frequency attenuation gradient profile along wells (red indicates high attenuation gradient, blue indicates low attenuation gradient).

attribute planar map derived from the frequency attenuation gradient method provides rich details of inter-well oil layers with clear boundaries, consistent with the structural hydrocarbon reservoir's feature of hydrocarbon enrichment at structural highs. The planar results show good agreement with actual well-log interpretations. Some peripheral wells located on structural slopes exhibit favorable hydrocarbon detection results, indicating potential oil-bearing prospects.

Based on well test data in the study area, statistics from 30 wells show that only 5 wells did not yield industrial oil flow, corresponding to areas with weak low-frequency energy variation rates. Meanwhile, well C904, located in an area of weak amplitude/low-frequency energy variation rate, obtained oil and gas shows. This may be related to C904 being primarily a fault-controlled lithologic reservoir. Statistics show that 6 out of 30 wells did not match, resulting in an overall coincidence rate of 80%. This demonstrates that using the low-frequency energy variation rate for hydrocarbon reservoir detection has high accuracy and feasibility.

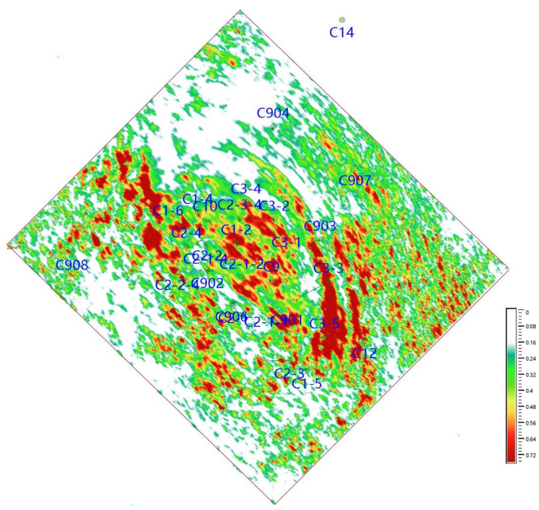


Figure 6. Frequency attenuation gradient attribute planar map for II6-II9 (red indicates high attenuation gradient, blue indicates low attenuation gradient).

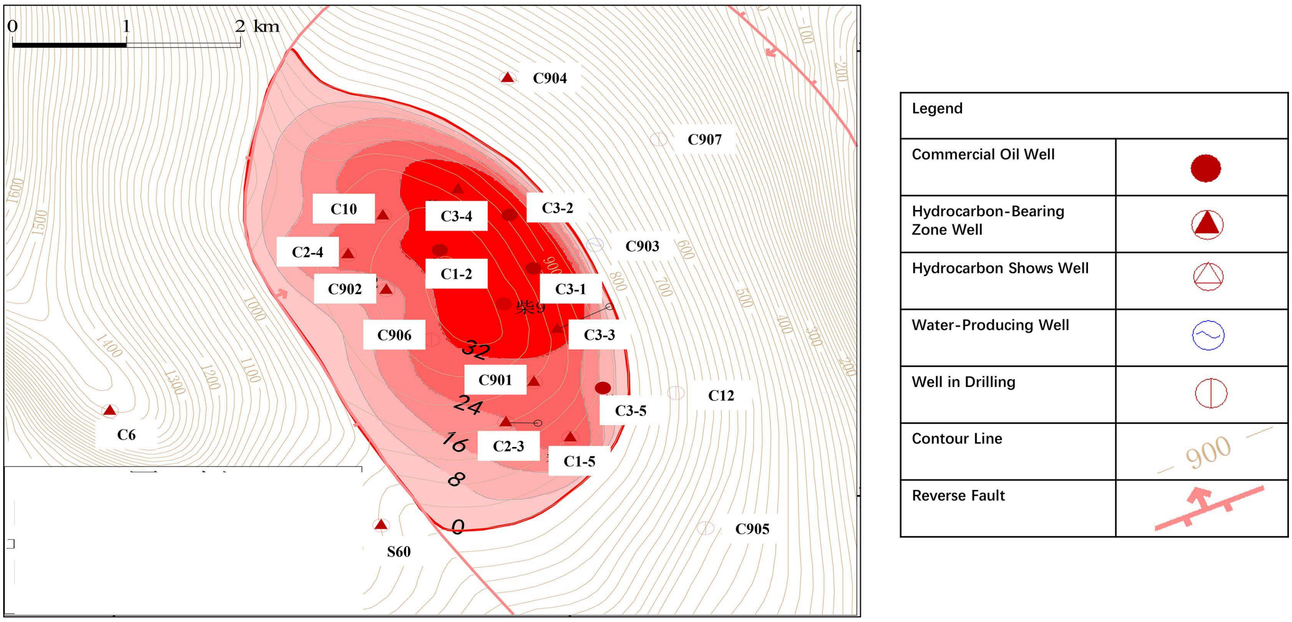


Figure 7. Oil layer thickness map for II6-II9.

4. Conclusion

Due to the complex lithology and seismic gather quality in the study area, conventional methods for predicting lithology, physical properties, and hydrocarbon-bearing characteristics through pre-stack inversion face significant limitations. Therefore, based on biphasic medium theory, a frequency variation gradient attribute method was proposed and tested on both simulation models and actual data. The results demonstrate that this method can qualitatively enhance hydrocarbon response features in seismic data, offering a new approach for hydrocarbon reservoir detection under similar geological conditions.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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