Identification Method of Mud Shale Fractures Base on Wavelet Transform

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Abstract. In recent years, inspired by seismic analysis technology, a new method for analysing mud shale fractures oil and gas reservoirs by logging properties has emerged. By extracting the high frequency attribute of the wavelet transform in the logging attribute, the formation information hidden in the logging signal is extracted, identified the fractures that are not recognized by conventional logging and in the identified fracture segment to show the "cycle jump", "high value", "spike" and other response effect is more obvious. Finally formed a complete wavelet denoising method and wavelet high frequency identification fracture method.

1. Introduction

As the reservoir space and migration channel of oil and gas, fractures play an important role in oil and gas exploration and development. The identification and evaluation of fractures has always been the focus of petroleum geology workers [1]. It is rich in organic matter mud shale and is an effective reservoir of oil and gas reservoir in the southeastern of Guizhou region. The organic matter abundance and thermal evolution are high, the fractures are more developed, and the deposition thickness is large, the shale gas resources have great potential. Therefore, it is very important to identify the shale fractures in this area.

Conventional logging method to identify the fractures obtained by the well logging response curve is often not intuitive and obvious, using imaging logging to identify the fractures although the effect is better, but the cost is high. For the use of logging data to identify the fractures, predecessors do a lot of research. Lu [2] (1998) summarized the conventional logging, artificial neural network and Stoneley wave and other fracture identification methods. Zhong [3] (2005) used electric imaging logging images and identified the type of fractures and the direction of paleo-stress in combination with core calibration. Yu (2006) used fractal attributes of logging attributes in the generation to evaluated fracture development degree and fracture development boundary of fractured reservoirs which has achieved the purpose of predicting the lateral fractures of reservoirs [4]. Sun (2013) through the comparative analysis of shale gas and coalbed methane, summarizes the "seven-property relationship" including logging properties to complete the logging evaluation of coalbed methane and shale gas [5]. Based on the theory of logging attribute analysis, the method of wavelet transform is used to identify the fracture, through the treatment of conventional logging information, the data distortion is eliminated, and the mud shale fissure information hidden from the strata is extracted to provide effective support for the prediction of reservoir fracture development.
2. Well Logging Response Characteristics of mud Shale fractures

Taking the TX1 well as an example, the frequency histogram (Fig.1) is drawn from the logging data of the deeper depth (1780.5m-1816.4m) developed in the south eastern of Guizhou region. The AC value range is in the range of 203.764-331.794μs/m, with an average value of 264.388μs/m. The GR ranges from 276.692-735.204 API with an average of 470.370API. The CAL range is 22.044-24.123cm, with an average value of 22.858cm and the RD is in the range of 28.201-1054.761OMM with an average of 516.649OMM.

![Figure 1. Several typical conventional logging curves](image)

The depth of the four shale reservoir fractures in the whole area is analysed and studied in the conventional logging curve (Fig.2, Fig.3).

As can be seen from the figure, at depth of 1784.2m-1784.5m and 1805.65m-1806.5m, the AC curve does not appear "cycle jump" phenomenon. The CNL curve did not show a significant increase compared to the non-fractured segment. Although the development of fractures leads to a decrease in rock density, the DEN curve values do not exhibit low or spike response. The RD and RS curve also exhibit high values in the fracture zone, only the low values appear in the natural gamma curve values.

At the depth of 1789.1m-1791.08m and 1796.3m-1799.2m, the AC curve appeared "cycle jump" phenomenon. The CNL and DNE log values are high compared to non-fractured segments. The resistivity logging value, especially the GR logging, is significantly higher, and the radioactive element logging response is also significant. It can be seen that different types of conventional logging data can reflect the response of fractures to a certain extent, and cannot accurately identify all the fractures, the accuracy and accuracy of the existence of defects.
Figure 2. The well response curve and core of the 1782m-1792m fracture section in the southeastern of Guizhou region of the TX1 well.

Figure 3. The well response curve and core of the 1794m-1816.4m fracture section in the southeastern of Guizhou region of the TX1 well.
As it can be seen that imaging logging can visually and accurately identify most of the fractures, but there are some errors in the interpretation of man-machine interaction. Due to the development of shale layer, causing interference, the phenomenon of plate misplaced, the imaging logging is not high quality and not clear. In the measurement accuracy, the imaging logging can detect fractures of 5mm in size, but some fractures in the corrugations and some of the fractures shown under electron microscopy are not shown on the imaging logs.

The wavelet transform can enhance the information of fractures in the reservoir, to a certain extent, to avoid this error. In order to more comprehensively highlight the fracture information, wavelet transform is a new research direction. This article makes an in-depth study on the logging information extracted by wavelet transform.

3. Wavelet transform mud shale fracture identification

The log signal is a continuous numerical sequence in the depth domain, if the depth domain is defined as the time domain, the logging data of the whole study section can be used as a continuous function analysis to extract various attribute parameters [6]. The identification of fractures is mainly reflected in the sudden change of the signal. Based on the actual situation of the study area and the logging data, the high frequency attribute of the wavelet transform is chosen to study the mud shale logging signal processing method.

As a constant window and the ever-changing calculation method, wavelet transform can be well suited for detecting mutated signal components in normal signals. Put any function in space under the wavelet base to start, the continuous wavelet transforms of any function $z(t)$ is [7]:

$$WT_z(a,b) = \langle z(t), \varphi_{a,b}(t) \rangle$$

$$= \frac{1}{\sqrt{a}} \int z(t) \varphi \left( \frac{t-b}{a} \right) dt$$

(1)

Where $WT_z(a,b)$ is wavelet transform coefficients; $a$, $b$ is scale parameters and translation parameters; $\varphi(t)$ is basic wavelet.

And $\varphi_{a,b}(t)$ is the first translation and telescopic of $\varphi(t)$. If $a$, $b$ continuous transformation can be a set of functions $\varphi_{a,b}(t)$ recorded as a wavelet basis function.

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \varphi \left( \frac{t-b}{a} \right)$$

(2)

As can be seen from the above formula, $a$, $b$ can represent the frequency band and time period. Wavelet transform has excellent analytical capability in local signal analysis.

3.1. High Frequency Attributes Based on Wavelet Transform

Wavelet multi-resolution analysis method is to use the scale function and wavelet function to construct a high-pass filter to extract the high-frequency signal to describe the details of the signal. And then further extract the high frequency details of the previously extracted low frequency signal, and repeat the above steps to achieve the desired processing effect [8].

Let the discrete sampling component of the logging signal $f(x)$ be $f(n)$ $(n = 1,2, \ldots n)$. According to the previous analysis, it can be considered that $f(x)$ is the approximation of the original signal at $j=0$, record as: $a_0(n) = f(n)$ [9]. The multiresolution decomposition algorithm is expressed as:

$$\begin{align*}
a_{j+1}(n) &= \sum_{k \in \mathbb{Z}} a_{j}h_0(k - 2n) \\
d_{j+1}(n) &= \sum_{k \in \mathbb{Z}} a_{j}h_1(k - 2n)
\end{align*}$$

(3)
\[ a_j(k) = \sum_n a_{j+1}(n) h_0(k - 2n) + \sum_n d_{j+1}(n) h_1(k - 2n) \] (4)

Where \( a_{j+1} \) is the low frequency function of \( a_j \); \( d_{j+1} \) is the high frequency function of \( d_j \); \( h_0(n) \), \( h_1(n) \) are the corresponding high and low pass filter coefficients corresponding to the wavelet function and scale function; \( j \) is a multiresolution resolution scale, which can also be called a multiresolution decomposition layer. Theoretically, as long as \( j \) satisfies a series of positive integers, it is possible to complete the multiresolution decomposition of the logging signal [10]. In the use of wavelet transform to extract high-frequency properties, wavelet basis function itself orthogonality, tight support, high vanishing moment order and other characteristics should be also taken into consideration.

3.2. Logging attribute analysis and treatment of shale fractures

In the use of conventional logging methods to identify the fractures, the AC signal is usually able to record the formation of fracture information, but the "cycle jump" and the peak, the time difference increases the characterization of a series of fractures is usually more vague and difficult to observe. Therefore, the high-frequency attribute extraction of the wavelet signal is carried out, and the shock information contained in the fracture information is recorded by the high-frequency attribute to amplify the characteristics of the oscillation to identify the fracture.

There are three main criteria for selecting wavelet bases: self-similarity principle, discriminant function and support length. Because Daubechies wavelet function has good tight support, smoothness and approximate symmetry [11], it is called the most widely used function in dealing with nonstationary logging signals. So Daubechies is chosen as the wavelet basis and the acoustic time difference curve is decomposed into four high frequency decomposition signals (Fig.4).

**Figure 4.** The 4 high frequency properties of AC curve

Combining with the conventional logging curve shows that the fracture is concentrated but the recognition effect is poor, and the original high frequency attribute is the best.

It is generally believed that when the crevice development, especially the low-angle slit and the mesh-like slit are very developed, the original AC curve has a cyclical jump phenomenon at the development of the fracture section due to the absorption of the acoustic energy itself, and due to the energy loss, the speed of sounds are slow down, the whole curve appears to increase the phenomenon
of time difference. As is clear from the figure (Fig.5), fractures in the whole Niutitang Formation are generally developed. In the actual acquisition of the AC logging signal, the original logging curve and the wavelet high frequency are more consistent for the identification of non-fractured sections. In the development of fractures, the frequency jump and the time difference increase are not obvious, but the wavelet high frequency attribute shows the phenomenon of frequency jump and time difference increase, which proves that the fractures are real. At the same time in the part of the fracture development section, conventional acoustic logging can show obvious characteristics. In particular, the high frequency properties extracted by wavelet multiresolution analysis show strong oscillatory characteristics (3,4) at the fracture development, and the effect of the fracture resistance on the resistivity signal is more obvious than the original resistivity signal. Therefore, the high frequency attribute extracted by wavelet transform can highlight the fracture information hidden in the logging signal.

Figure 5. Comparison of Wavelet High Frequency Curve and Conventional Logging (1757m-1816.4m)

4. Conclusion
(1) Conventional logging and imaging logging can solve most of the problems of slime fissure information identification, in which AC, GR, CAL and RD logging method are particularly prominent for the identification of shale fractures. The AC curve shows "cycle jump" phenomenon, the CNL curve value increases obviously compared with the non-fractured segment, DEN values appear low or spike response, RD logs also appear high in the fracture section. But for some of the existence of noise interference logging signal recognition is poor, the lack of information on the hidden fractures in the signal extraction.

(2) According to Daubechies wavelet base which it has the characteristics of support, smoothness and approximate symmetry. through the high frequency attribute extraction of wavelet transform, the sound wave time difference signal is decomposed into four high frequency signals, the whole Niutitang Formation was identified, and the fracture information was extracted and compared with the original acoustic signal. The high-frequency signal of the level3 is outstanding, not only consistent with the curve characteristics of the fractures section identified by the conventional logging, but also extracts the fracture information hidden in the curve accurately in the depth of the fracture that is not recognized in the conventional logging. It is consistent with the result of the microscopic photograph. Which shows the characteristics of mud shale development in the Niutitang Formation.
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