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A study of wavelet transforms applied for fracture identification and fracture density evaluation

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Abstract: Combining wavelet transforms with conventional log differential curves is used to identify fractured sections is a new idea. In this paper, we first compute the mother wavelet transform of conventional logs and the wavelet decomposed signals are compared with fractures identified from image logs to determine the fracture-matched mother wavelet. Then the mother wavelet-based decomposed signal combined with the differential curves of conventional well logs create a fracture indicator curve, identifying the fractured zone. Finally the fracture density can be precisely evaluated by the linear relationship of the indicator curve and image log fracture density. This method has been successfully used to evaluate igneous reservoir fractures in the southern Songnan basin and the calculated density from the indicator curve and density from image logs are both basically consistent.
Keywords: Wavelet transform, fracture identification, differential curves, fracture density

Introduction

Igneous reservoirs are a new field in oil and gas exploration and many researchers have contributed to this field. Pan et al. (2008) proposed the QAPF classification based on the IUGS and determined the volcanic rock mineral content using a genetic algorithm based on well logs. Wu et al. (2008) analyzed the seismic response of two immiscible fluids in saturated porous media by the Santos three-phase porous rock physics model and proposed that in low-porosity and low-permeability igneous reservoirs the pressure and shear waves frequency dispersion could be ignored. Gas in the pores has little effect on the pressure and shear wave ratio but with a certain water saturation the porosity affect is significant. Li et al. (2009) calculated the matrix porosity of fractured and vuggy reservoirs, such as volcanics and weathered dolomite, using an empirical formula from full diameter rhyolite core experiments and indicated that this formula was suitable for both acidic volcanic reservoirs and medium-basic volcanic and weathered dolomite when the porosity is from 1.5% to 15%. The abnormal responses are usually observed on well log curves because the fractures might change a few reservoir rock characteristics, such as resistivity, elasticity, and radioactivity to some degree. Therefore, a variety of methods for identifying fractures using conventional well log data were invented, such as DLL-separation, radioactive-U, and elliptical holes, and etc. based on single or dual log curves (Wang, 1992; Pan et al, 2003).

The dip meter and image logs can be used to evaluate fracture parameters more accurately. However, they are not commonly used. In this case, precisely evaluating the fracture parameters with conventional well log data becomes difficult and a critical point in the study of fractured reservoirs. Recently, the wavelet transform is a common approach used by many researchers who work on similar problems. Sahimi and Hashemi

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(2001) applied wavelet transforms on porosity logs and proposed that fractures could be indicated by the processed log responses at high frequencies. Yue and Tao (2006) extracted reservoir fluid properties using the wavelet transform method. Dutta et al. (2007) identified the fracture zones by analyzing shear waves. Mohebbi et al. (2007) was successful detecting fractures from a few wells through wavelet transforms of the log data. Tokhmechi et al. (2009) proposed that the decomposed signal, corresponding to the fracture density from image logs, can be found by wavelet transform of conventional well logs in the low frequency range. By establishing a relationship between the decomposed signal and the fracture quantity in the fractured zone, the fracture density is possible to be approximately evaluated.

By focusing on the study of fractured igneous reservoir, in this paper the decomposed signals were first obtained using a wavelet transform on conventional well logs. Then the fractures were identified with a fracture indicator curve which is unique and established by linearly combining the wavelet decomposed signal and the differential curve. As a result, the fracture density is estimated relatively accurately by its quantitative correlation with the fracture indicator curve. Our method was applied and proven in five wells in the southern Songnan basin.

Wavelet transform characteristics and application on conventional well logs

Wavelet transforms are a time-frequency localization analytical method with fixed size and variable window shape with variable time and frequency windows. It is suitable for detecting abrupt signals in the normal signal. A wavelet transform exhibits multiple resolutions (multi-scale) and can be used to observe signals at a different scale (from rough to fine). The wavelet transform has the ability to characterize localized signal features in both time and frequency domains by choosing the mother wavelet appropriately (Gao et al., 2008).

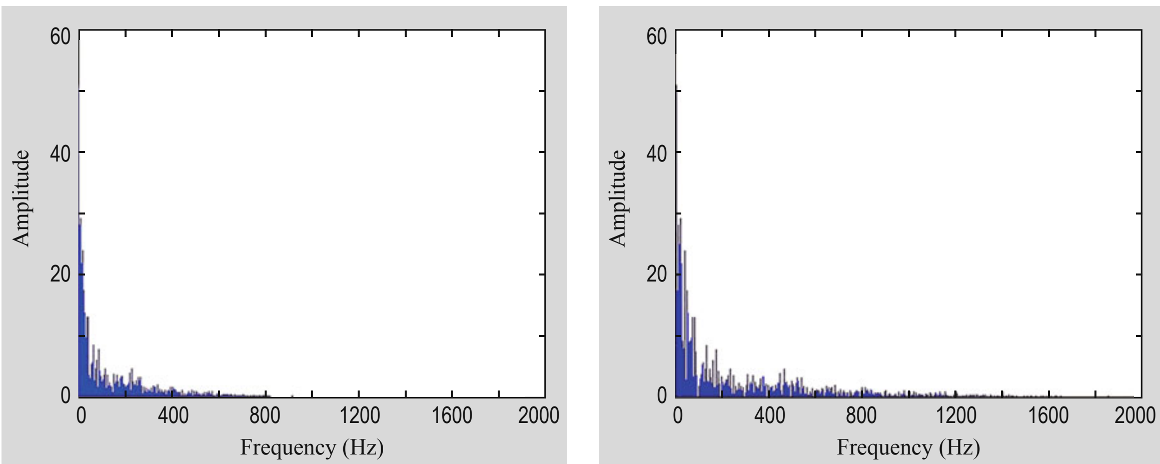
By expanding an arbitrary function $z(t)$ in $L^2(R)$ space under the mother wavelet, the continuous wavelet transform of $z(t)$ is obtained (Ge and Chen, 2006):

$$WT_z(a,b) = < z(t), \varphi_{a,b}(t) > = \frac{1}{\sqrt{a}} \int_R z(t) \varphi(\frac{t-b}{a}) dt, \quad (1)$$

where a and b represent the scale and translation parameters, respectively. $WT_z(a,b)$ is the wavelet transform coefficients. In this study, $z(t)$ is the well log curve processed by wavelet transform and $\varphi(t)$ is the chosen mother wavelet function.

Signal energy analysis

In our study, the dominant frequency is determined by transforming the signal using Fourier transform from depth to frequency and then the signal is analyzed using different mother wavelets. Figure 1 shows the energy analysis of the density log data of Well A in the study area. Figure 1a illustrates the signal Fourier transform over the entire frequency domain and Figure 1b shows the transform from 0 to 1000 Hz. It is clear that the major signal energy distributes in the low frequencies so, as a result, the mother wavelet analysis of the signal will be studied at low frequencies.



(a) All frequencies (b) 0 to 1000 Hz

Fig. 1 Density log energy analysis in Well A.

Wavelet transform on conventional well logs

Conventional well log curves contain the reservoir fracture response, so we apply various wavelet transformations on conventional well log curves. By comparing the decomposed signal with the fracture density extracted from image logs, identifying the optimum decomposed signal, and then combining with the differential curve to identify the fractures.

Using equation (1), the decomposed signals are obtained by applying the mother wavelet transform (Tokhmechi et al., 2009) on the conventional log curves in five wells. We find that bior4.4 and coif5 are the desirable wavelets after comparing the decomposed signals with the fracture densities. In detail, bior4.4 is the suitable mother wavelet for density curves from four of the wells and coif5 matches with the resistivity curve from a single well.

Figure 2 shows the decomposed signal curves by bior4.4 wavelet transforms on the density curve and the fracture density curve from image logs in Well A. The decomposed signals d1 to a5 which range from low to high frequency are obtained by bior4.4 wavelet transform on the density curve (left-most curve). The right curve is the fracture density extracted from the resistivity image log and the right panel is the formation micro-resistivity image (FMI) with red lines indicating the fractures. By comparison, we find that the decomposed signal curve d5 has some corresponding characteristics with the fracture density curve. In the densely fractured interval, generally the d5 curve has a larger response. However, the d5 curve alone does not show all the information of the fractured zone.

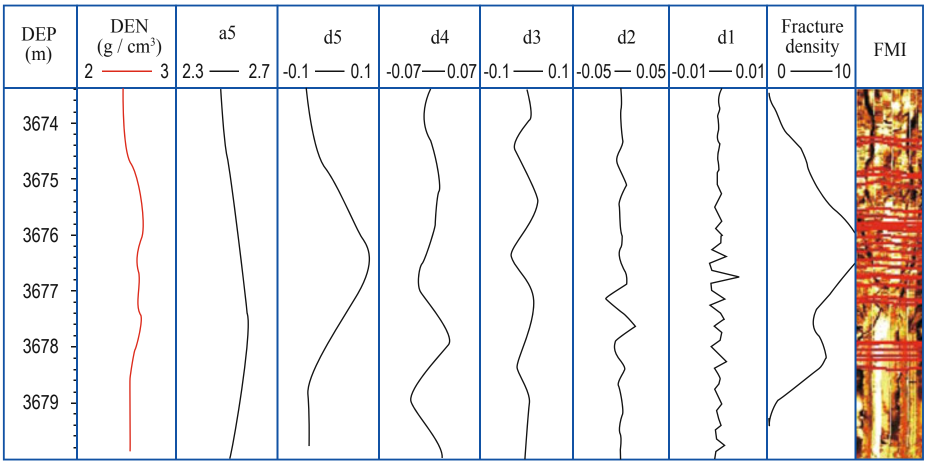


Fig. 2 Comparison of the decomposed signal curves using the bior4.4 mother wavelet transform on the density log in Well A and the fracture density curve from the image log.

Establishing the generalized fracture indicator curve

Establishing a single fracture indicator curve

Since both the wavelet decomposed conventional log signal and the conventional log differential curve can reflect the fractures to some extent, a single fracture indicator curve can be found. From the well log map, the wavelet decomposed signal d5 values at t_b and t_f correspond to tight and fractured zones, respectively. The fracture indicator curve of the wavelet decomposed signal at a certain depth interval is:

$$P_1 = (t - t_b)/(t_f - t_b), \tag{2}$$

where t stands for the d5 data being wavelet transformed and t_b and t_f stand for the wavelet decomposed signal d5 values corresponding to tight and fractured zones.

Similarly, fracture indicator curve given by the conventional log differential curve can also be established as:

$$P_2 = (\Delta C - \Delta C_b)/(\Delta C_f - \Delta C_b), \tag{3}$$

where ΔC is the differential curve value and ΔC_b and ΔC_f stand for the differential curve values corresponding to tight and fractured zones, respectively.

Establishing a generalized fracture indicator curve

Although the wavelet decomposed signal and conventional log differential curve can both reflect fractures to some extent, the two methods reflect the fractures to a different extent, so it is reasonable to identify fractures using the two methods simultaneously. Based on the fracture extent, the two curves are weighted by their responses to the fractures and a generalized fracture indicator curve P is generated:

$$P = c(t - t_b)/(t_f - t_b) + d(\Delta C - \Delta C_b)/(\Delta C_f - \Delta C_b), \quad (4)$$

where *c* and *d* are the control variables associated with contributions of the d5 curve and differential curve to the indicator curve, respectively. As the differential density curve better reflects the fractures, we select the differential density curve and wavelet transform to find the indicator curve in this paper.

Calculation of the control variables

For the purpose of finding an accurate fracture indicator curve, multiple regression analysis is applied to calculate c and d in equation (4). First we set up a linear regression equation and consider a bivariate linear regression equation with dependent variable y to independent variables x_1, and x_2:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2, \quad (5)$$

where b_0, b_1, and b_2 should let the factual observation data y and regression estimate $\hat{y}$ be a minimal sum of deviation squares.

Computing the extreme value of the multivariate function based on differential calculus, the following equations can be obtained:

$$b_1 = \frac{(n\sum_{i=1}^{n} x_{2i}x_{1i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{1i})(\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_{2i} - n\sum_{i=1}^{n} y_i x_{2i}) - (n\sum_{i=1}^{n} x_{2i}x_{2i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{2i})(\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_{1i} - n\sum_{i=1}^{n} y_i x_{1i})}{(n\sum_{i=1}^{n} x_{1i}x_{1i} - \sum_{i=1}^{n} x_{1i}\sum_{i=1}^{n} x_{1i})(n\sum_{i=1}^{n} x_{2i}x_{2i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{2i}) - (n\sum_{i=1}^{n} x_{1i}x_{2i} - \sum_{i=1}^{n} x_{1i}\sum_{i=1}^{n} x_{2i})(n\sum_{i=1}^{n} x_{2i}x_{1i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{1i})}, \quad (6)$$

$$b_2 = \frac{(n\sum_{i=1}^{n} x_{1i}x_{1i} - \sum_{i=1}^{n} x_{1i}\sum_{i=1}^{n} x_{1i})(\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_{2i} - n\sum_{i=1}^{n} y_i x_{2i}) - (n\sum_{i=1}^{n} x_{1i}x_{2i} - \sum_{i=1}^{n} x_{1i}\sum_{i=1}^{n} x_{2i})(\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_{1i} - n\sum_{i=1}^{n} y_i x_{1i})}{(n\sum_{i=1}^{n} x_{2i}x_{1i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{1i})(n\sum_{i=1}^{n} x_{2i}x_{1i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{1i}) - (n\sum_{i=1}^{n} x_{2i}x_{2i} - \sum_{i=1}^{n} x_{2i}\sum_{i=1}^{n} x_{2i})(n\sum_{i=1}^{n} x_{1i}x_{1i} - \sum_{i=1}^{n} x_{1i}\sum_{i=1}^{n} x_{1i})}, \quad (7)$$

Let

$$b_1 = a \bullet c, \quad (8)$$

$$b_2 = a \bullet d, \quad (9)$$

$$c + d = 1. \quad (10)$$

where *a* is a constant. By equations (8), (9), and (10) as a simultaneous equations the constant a can be eliminated to get

$$c = \frac{b_1}{b_1 + b_2}, \quad (11)$$

$$d = \frac{b_2}{b_1 + b_2}, \quad (12)$$

where x_1 and x_2 in the equations (7) and (8) are the fracture indicator curve values given by the wavelet decomposed signal and differential curve, respectively, *c* and *d* are the control parameters, and *a* is a constant.

Combine the differential curve with wavelet transform to identify the fractured interval

The differential curve (Sun et al., 1999) reflects the log curve changes and exhibits large variations in the fractured igneous zone but it is also greatly affected by factors such as borehole conditions, reservoir physical properties, and etc. so it would generate errors if fractures are identified using the differential curve alone. The wavelet transform has multiple scale characteristics and the signal extraction relies on the scale selection. However it is slightly affected by borehole conditions, reservoir physical properties, and etc. so the combination of differential curve and wavelet transform can identify the fractured interval more accurately.

Fracture identification and fracture density evaluation

In this study, neutron and density differential log curves are combined with the wavelet transform to identify fractured zones. Figure 3 is a log interpretation chart for a fractured section of igneous rock in Well A. The right chart is the FMI image, from which we see that the reservoir interval 3675.5 to 3677.5 m has higher fracture density than the depths from 3674 to 3675 m and from 3678 to 3679 m. The deeper interval has a higher fracture density than the shallower in the differential curve and the d5 curve is too flat in the deeper section, and so the fracture indicator curve P generated by combining the differential curve and wavelet transform using weighting can identify the fractured interval. In addition, the c and d values from equations (11) and (12) are 0.65 and 0.35, respectively.

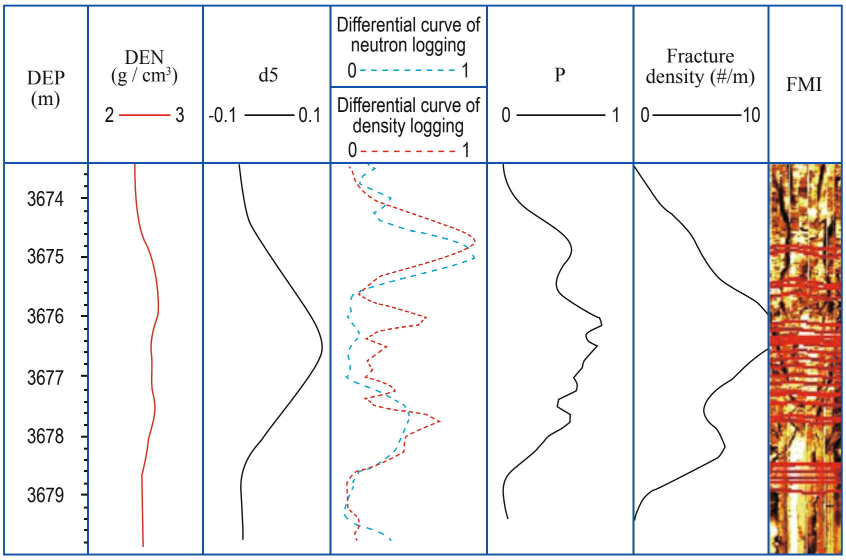


Fig. 3 Identification of the igneous reservoir fractured interval in Well A.
From left to right, track 1 is the well depth, track 2 is the density log curve, track 3 is the d5 curve obtained by the transformed density curve, track 4 is the differential curve, track 5 is the generalized fracture indicator curve, track 6 is the fracture density extracted from resistivity image log, and track 7 is the FMI image.

Calculation of fracture density

The linear relationship between the fracture indicator curve and the fracture density from image logging has been determined by regression analysis on 152 samples in Well A as

$$F = 12.455 \times \mathrm{P} - 0.717, \qquad (13)$$

where P is fracture indicator curve and F is the calculated fracture density.

Figure 4 is a cross-plot of the fracture density from image logging and the calculated fracture density c. It shows that when the fracture density is less than 1, the well log response is not obvious and leads to a large error in the calculated fracture density. When the fracture density is greater than 1, the error is small with a mean relative error of 0.53 through error analysis.

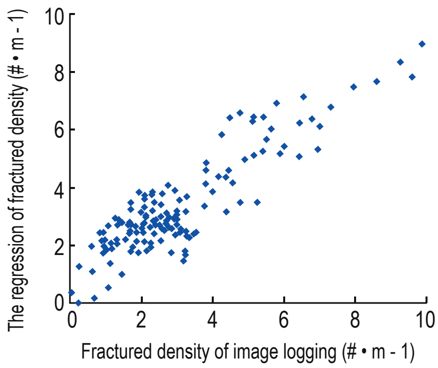


Fig. 4 Crossplot of the fracture density from the image log and the calculated fracture density from the fracture indicator curve in Well A.

Conclusions

The determination of fracture parameters is a difficult and critical part of reservoir fracture evaluation. In this paper, with wavelet transformation of the conventional log curves, the wavelet decomposed signal which best matched the fractures was found. However the fractures cannot be indicated completely by an appropriate mother wavelet transform of conventional well logs. The combination of wavelet transform and differential curve forms a generalized fracture indicator curve to make up for this drawback to some extent, improves the reliability of calculating fracture density, and provides a basis for classifying the fracture density.

The fracture indicator curve can calculate the fracture density sufficiently well but it is also a relatively better indication of the fractures owing to fracture distribution characteristics such as randomness, inhomogeneity, and special filtration. The research on five wells in the Changling fault depression in north-eastern China shows that the proposed method is effective when the fracture density is greater than 1 and it shows good correspondence between the calculated fracture density and the density from image logs.

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