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# Pre-stack-texture-based reservoir characteristics and seismic facies analysis*

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**Abstract**: Seismic texture attributes are closely related to seismic facies and reservoir characteristics and are thus widely used in seismic data interpretation. However, information is mislaid in the stacking process when traditional texture attributes are extracted from post-stack data, which is detrimental to complex reservoir description. In this study, pre-stack texture attributes are introduced, these attributes can not only capable of precisely depicting the lateral continuity of waveforms between different reflection points but also reflect amplitude versus offset, anisotropy, and heterogeneity in the medium. Due to its strong ability to represent stratigraphics, a pre-stack-data-based seismic facies analysis method is proposed using the self-organizing map algorithm. This method is tested on wide azimuth seismic data from China, and the advantages of pre-stack texture attributes in the description of stratum lateral changes are verified, in addition to the method's ability to reveal anisotropy and heterogeneity characteristics. The pre-stack texture classification results effectively distinguish different seismic reflection patterns, thereby providing reliable evidence for use in seismic facies analysis.
**Keywords**: Pre-stack texture attributes, reservoir characteristic, seismic facies analysis, SOM clustering, gray level co-occurrence matrix

## Introduction

In seismic exploration, seismic facies are defined as stratigraphic units that have certain reflection characteristics. Therefore, the analysis of seismic facies is necessary for sedimentary facies interpretation and inference. Early seismic facies classification was conducted manually; however, as this method involves subjectivity, it is not suitable for large-scale seismic data analysis. Computer techniques are therefore used to extract information pertaining to valid geologic features and uncover seismic reflection patterns through pattern recognition techniques. Seismic facies analysis can then be achieved by combining such information with that obtained from wells and related material; this is the most popular seismic facies classification technique used globally as it is rapid, quantitative, and objective (Han et al., 2011; Saraswat and Sen, 2012; Chopra and Marfurt, 2014).

The use of seismic facies classification techniques has been steadily increasing in hydrocarbon prediction

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processes over the past 20 years, and a large number of analysis methods is available for application in automatic interpretation. For example, West et al. (2002) employed seismic texture attributes and neural networks to generate seismic facies using an interactive approach. de Matos et al. (2006) detected the modulus maxima line amplitudes of trace singularities using the wavelet transform technique in unsupervised seismic facies analysis. This technique has the advantage of being less sensitive to horizon interpretation noise. Roy (2013) reported the use of a combination of different attributes for a self-organizing map (SOM) and generative topographic mapping in seismic facies analysis. In addition, Gao (2011) proposed the texture model regression method for seismic waveform characteristics in seismic facies analysis. Furthermore, Du et al. (2015) de-noised seismic data using the empirical mode decomposition method, where the reconstructed waveform serves as the input for the SOM algorithm to perform seismic facies analysis.

With increasing difficulties faced in exploration, the difficulty in using the conventional post-stack-data-based seismic facies analysis technique increases in complex lithologic stratigraphic reservoir exploration. Thus, it is necessary to analyse the reservoir by using prestack seismic data which carries abundant stratigraphic and depositional information. An amplitude versus offset (AVO) feature contained in pre-stack data can be used to identify fluid, lithology, and anisotropic characteristics, which can effectively reduce the uncertainty of reservoir prediction, and thus improve the discrimination ability of reservoir physical properties and hydrocarbon content and assist in the analysis of reservoir characteristics. However, the final stacking wavelet could be distorted because of different offsets. Thus when the anisotropy or AVO features exist in a reservoir, subtle lateral variation characteristics are missed, and analysis of the fine-grained seismic reflection structure is not possible.

Some researchers have used pre-stack seismic data in seismic facies analysis. For example, West at al. (2002) determined that AVO characteristics could be used as an auxiliary feature in seismic facies analysis and that they assisted in complex reservoir identification. Kourki and Riahi (2014) proposed a SOM algorithm to cluster pre-stack data for seismic facies analysis in relation to the existence of the AVO feature. In addition, Song et al. (2015) performed seismic facies analysis based on wide azimuth gathers and CMP traces, and Marfurt (2014) predicted that the method used in pre-stack data analysis would be the future research trend. It is thus considered that pre-stack-data-based seismic facies analysis will become an important research hotspot.

Due to the development of seismic acquisition techniques in a wide azimuth, wide band, high density, and full wave field, and in relation to progress made in seismic data processing technology, the quality of pre-stack seismic data has greatly improved. After processing, a variety of pre-stack gathers with high signal to noise ratio can be formed, such as CMP gathers, angle gathers, wide azimuth gathers, and such high quality data sets provide excellent materials for pre-stack seismic facies analysis.

To analyze seismic facies using pre-stack seismic data, it is necessary to extract properties that are representative of geological characteristics. Seismic texture attributes describe the reflection characteristics of strata and utilize the space change feature of amplitude. The gray level co-occurrence matrix (GLCM) is the most common method used to extract texture attributes (Yenugu et al., 2010; Gao, 2011; Eichkitz et al., 2015), and Chopra and Alexeev (2006) confirmed that the GLCM can be used to describe the continuity of post-stack sections and different reflection patterns. Gao (2003) extended the GLCM to three dimensions post-stack data for extracting texture in a greater number of directions, and this assisted in visualizing and detecting major structural and stratigraphic features. In addition, because of the superiority of texture, de Matos et al. (2011) used various textural properties to analyze seismic facies and describe channels.

In this paper, we propose the use of the GLCM to extract texture attributes from pre-stack seismic data. In this respect, pre-stack textures have two advantages. First, both pre- and post-stack textures can be used to analyze waveform changes between different points. However, when a medium is inhomogeneous or has AVO characteristics, the stacking process distorts the final stacking wavelet and misses certain information because of the amplitude variance of traces from a common reflection bin. Pre-stack textures that represent lateral changes in the same azimuth or offset can finely describe the trace amplitude changes among different reflection points. Second, pre-stack textures can describe features of variation in traces from a common reflection bin. For CMP gathers, pre-stack textures represent the AVO characteristics of a reservoir. For wide azimuth gathers, pre-stack texture can be used to research anisotropic characteristics and heterogeneity of a medium.

Pre-stack texture attributes are a combination of the pre-stack wave shape, amplitude, continuity, and reservoir characteristics, and they describe the reflection characteristics of pre-stack seismic data. We can find different pre-stack reflection patterns by classifying pre-stack texture attributes that are closely related to a seismic facies. A pre-stack reflection pattern based on a seismic facies can reduce the multi-solution of explanation, which is beneficial to complex reservoir analysis, and can ultimately assist in the analysis of a sedimentary environment. Therefore, in this paper we propose a seismic facies analysis method based on seismic data using a combination of multi-directional pre-stack texture attributes and a SOM clustering algorithm. In this respect, we first describe the method used to extract the pre-stack texture attributes and then illustrate the significance of the pre-stack texture using synthetic trace gathers. We then present the procedure involved in seismic facies analysis using pre-stack texture. In the final section, an analysis of real seismic data is presented.

## Method used to extract pre-stack texture attributes

The workflow for pre-stack texture attribute extraction is shown in Figure 1. For each reflection point, we first extract the texture element using the neighboring reflection waveforms and the current waveform within a time window. The GLCM can then be built based on the texture element, and the texture attributes are then subsequently computed for a reflection point. The texture volume can be finally formed after conducting a rough analysis of all reflection points. In the following part of this section, we discuss the key parts involved in the process of texture attribute extraction.

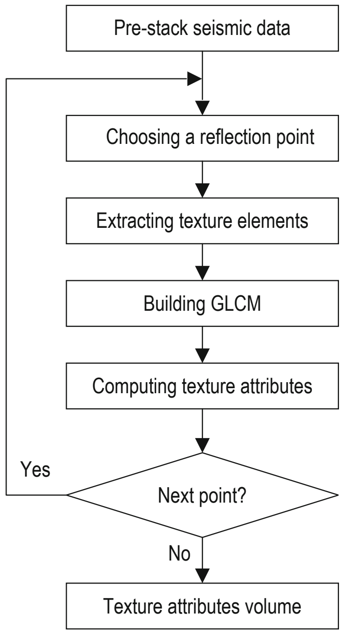
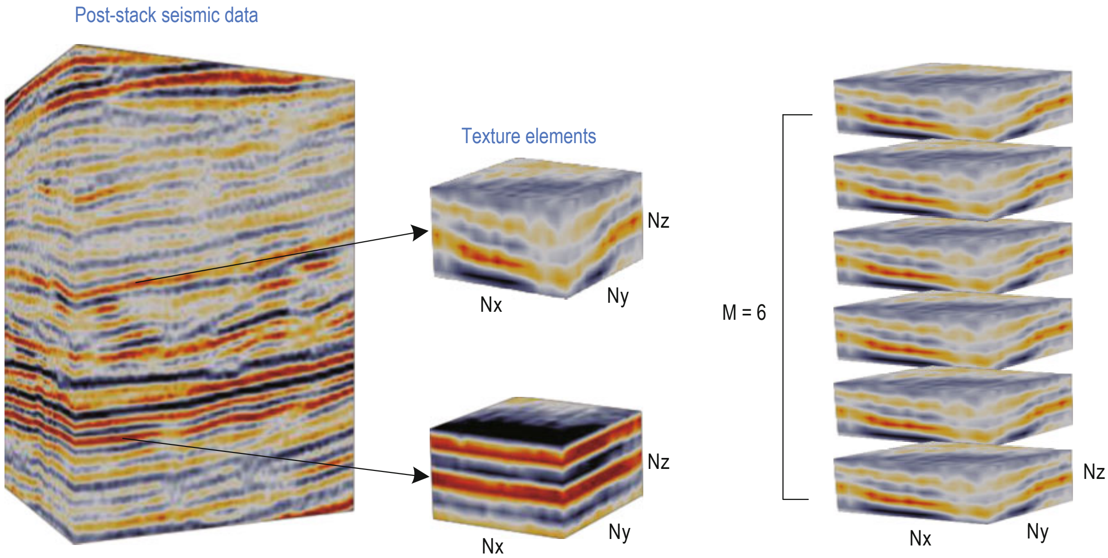



**Fig.1 Workflow involved in computing texture attributes volume.**

### Texture elements

The traditional seismic texture attribute is evaluated in post-stack data by analyzing an array of neighboring reflection amplitudes known as the texture element (Figure 2a), which is a mini-cube with a volume of Nx, Ny, Nz in the inline, crossline, and time directions, respectively. Thus, the pre-stack texture element is a




(a) Texture elements for post-stack data (b) Texture element for pre-stack data

**Fig.2 Seismic texture elements.**

four dimensional data cube (Figure 2b). M denotes the number of traces from one reflection point; for example, M = 10 for super gathers with 10 offsets and M = 6 for wide azimuth gathers with six azimuths. In this paper, we propose a novel approach for extracting the texture element based on pre-stack seismic data.

The workflow involved in texture element extraction is shown in Figure 3. Dip is utilized to extract the texture element for selecting adjacent reflection points to reduce the influence of the stratigraphic structure (Chopra and Marfurt, 2007). We use the coordinates (X, Y, and Z) to represent the spatial position of the current reflection point, and use (Xi, Yi, Zi) to represent the position of the adjacent reflection points. In addition, the same window size is used for all reflection points to truncate traces, thus resulting in the pre-stack texture element.

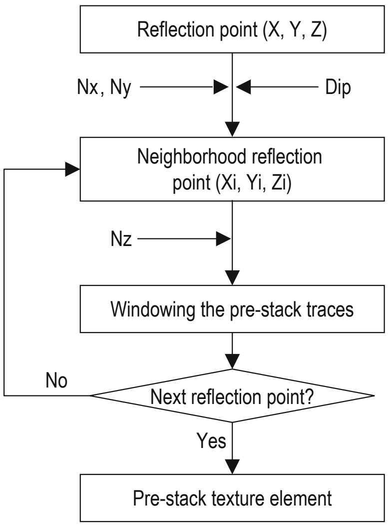



**Fig.3 Workflow involved in extracting pre-stack texture element.**

**Table 1 Parameters for texture elements**

| Parameters | Meaning |
|---|---|
| Nx = Ny >> Nz | Emphasis on lateral variation |
| Nx = Nz >> Ny | Inline section analysis |
| Ny = Nz >> Nx | Crossline section analysis |
| Nx = Ny << Nz | Characterizing waveform shape |

By selecting different parameters, Nx, Ny, and Nz, we can obtain pre-stack texture elements of differing sizes, thereby emphasizing the neighborhood waveform change characteristics in different dimensions and implying different significances, as shown in Table 1. Typically, Nx and Ny range from 3 to 9, and Nz is related to the sampling points in a period of the waveform (Gao, 2003; Gao, 2007). However, as relatively small parameters improve the resolution of the texture attribute but are sensitive to noise, the appropriate parameters need to be chosen according to the actual needs and the signal-to-noise ratio of the seismic data.

## GLCM

The GLCM is a statistical method used to examine texture that considers the spatial relationship of pixels (Figure 4 shows the process of building the GLCM using two dimensions data). The GLCM calculates how often pairs of pixel with specific values and in a specified spatial relationship occur in the origin data. In the GLCM along the x direction, element (1, 1) contains the value 3 because there are three instances in the 2D input data where two horizontally adjacent pixels have the values 1 and 1. However, there are no different values along the x direction, which causes the elements of the GLCM to lie on a diagonal. In addition, the distribution of elements along the y direction is deviated to the diagonal.

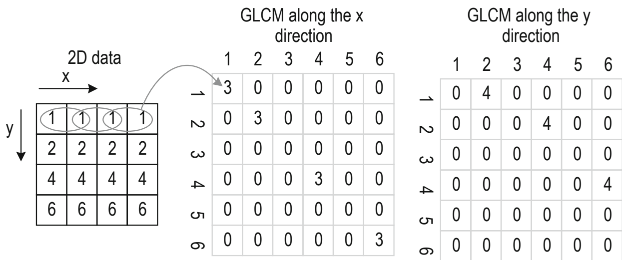



**Fig.4 GLCMs for 2D data.**

We propose that the GLCM can be used to describe the amplitude change relations in the pre-stack texture element that are represented in features of the pre-stack seismic data, and that these can be used to infer the reflection pattern. It is necessary to normalize the seismic data to Ng levels using the maximum absolute value in the texture element. The normalized element value D(x,y,z,m) is calculated by the following (de Matos et al., 2011)

$$D_{(x,y,z,m)} = Round\left(0.5*\left(\mathrm{Ng}-1\right)*\left(\frac{K_{(x,y,z,m)}}{K_{max}}+1\right)+1\right), (1)$$

$$K_{max} = \max_{x,y,z,m} K_{(x,y,z,m)},$$
$$0 \le x \le \mathrm{N_x}, 0 \le y \le \mathrm{N_y}, 0 \le z \le \mathrm{N_z}, 0 \le m \le \mathrm{M}, \quad (2)$$

where $K_{(x, y, z, m)}$ is the amplitude at sample location ($x$, $y$, $z$, $m$) in the pre-stack texture elements, and Round () is the function for computing the integral value.

The direction $\vec{w}$ of GLCM statistics can be represented by the vector ($W_x$, $W_y$, $W_z$, $W_m$) because of the four dimensions of the pre-stack texture elements. We definite the GLCM elements $E(i, j)$ as follows ,

$$E(i,j)=\sum_{x=1}^{N_x}\sum_{y=1}^{N_y}\sum_{z=1}^{N_z}\sum_{m=1}^{M}\left\{D_{(x,y,z,m)}=i,D_{(x,y,z,m)\pm\vec{w}}=j\right\}. \quad (3)$$

There are four typical statistical directions (1,0,0,0), (0,1,0,0), (0,0,1,0), and (0,0,0,1), that describe the variation characteristics along the inline, crossline, and time, and in the traces from the common reflection bin. To obtain texture attributes that are more robust, we define a set, W, for the statistical direction in formula (3) by setting $\vec{w}\in \mathrm{W}$. $E(i, j)$ is the number of pairs $(i, j)$ in all directions. For example, the value of W can be set as {(0,1,0,0), (1,0,0,0), (1,1,0,0), (1,-1,0, 0)} to extract the variation between the different reflection points.

## Texture attributes

By converting the statistic value, $E(i, j)$, of the GLCM into a probability value, $P_{ij}$, the texture attributes can be computed using the following formula (Gao, 2011),

$$P_{ij}=E(i,j)*\left(1/\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}E(i,j)\right). \quad (4)$$

The commonly used attributes are

$$Contrast=\sum_{i}^{Ng}\sum_{j}^{Ng}P_{ij}\left(i-j\right)^{2}, \quad (5)$$

$$Dissimilarity=\sum_{i}^{Ng}\sum_{j}^{Ng}P_{ij}\left\|i-j\right\|, \quad (6)$$

and

$$Homogeneity=\sum_{i}^{Ng}\sum_{j}^{Ng}\frac{P_{ij}}{1+\left(i-j\right)^{2}}. \quad (7)$$

Texture attributes describe the waveform amplitude variation in texture elements. When amplitude variations in the texture elements are large, the elements drifting from the diagonal of the GLCM have higher values. Thus, contrast and dissimilarity are large and homogeneity is small. However, although these three attributes describe the change of waveforms their relationship is not linear, and thus a variety of texture properties are usually required to describe the reflection characteristics of a reservoir.

# The meaning of pre-stack texture

We use the GLCM method to extract the texture attributes from pre-stack seismic data. Locations with large lateral contrast at different reflection points indicate a chaotic reflection structure, whereas small contrast shows continuity in the stratigraphy of the location. When the contrast is larger in the time direction it indicates that the wave impedance of the corresponding location is bigger, and that it forms a strong amplitude reflection configuration. The lateral contrast of amplitude in the pre-stack traces from common reflection bins reflects the reservoir characteristics (AVO, anisotropy, or medium heterogeneity). Specifically, for wide azimuth gathers, high contrast shows that the media has a strong anisotropy medium or strong heterogeneity. However, for CMP gathers, different contrasts describe diverse fluid properties.

To illustrate that pre-stack texture can carefully describe amplitude change between different points, we generate wide azimuth gathers and post-stack traces for two points. Given that offset factors “A” are related to offset, and that modulation factors “B” are associated with offset and fracture characteristics, the relationship between amplitude and the angle $\theta$ between the measuring direction and the fracture direction is (Mallick et al., 1998):

$$\mathrm{R}(\theta)=\mathrm{A}+\mathrm{B}\cos 2\theta. \quad (8)$$

Figure 5a shows the reflection coefficient at two reflection points, points A and B, with the same intensity of fractures but a different orientation of fracture development. Figures 5b and 5c are wide azimuth gathers and post-stack traces for two points, respectively. The gray level of the co-occurrence matrix is used to measure waveform change characteristics between the two reflection points, based on pre- and post-stack data, respectively. Figure 5d shows the GLCM from pre-stack gathers and Figure 5e shows the GLCM from post-stack traces. It is evident that contrast is higher in pre-stack and that it is lower in post-stack. The results show that the different of two reflection points can be reflected by the texture of pre-stack data and can therefore finely depict the lateral variation characteristics of waveforms.

The lateral contrast of amplitude in the pre-stack traces from the common reflection bin has a different meaning for the various trace gathers. Lateral variation reflects AVO attributes in CMP gathers and angle gathers, and the anisotropic characteristics in wide azimuth gathers with high quality. To illustrate the effectiveness of the GLCM in extracting AVO characteristics and anisotropy, we utilize the Zoeppritz equation to generate angle gathers, and equation (8) to generate wide azimuth gathers, which is used for texture extraction from the reflection bin.

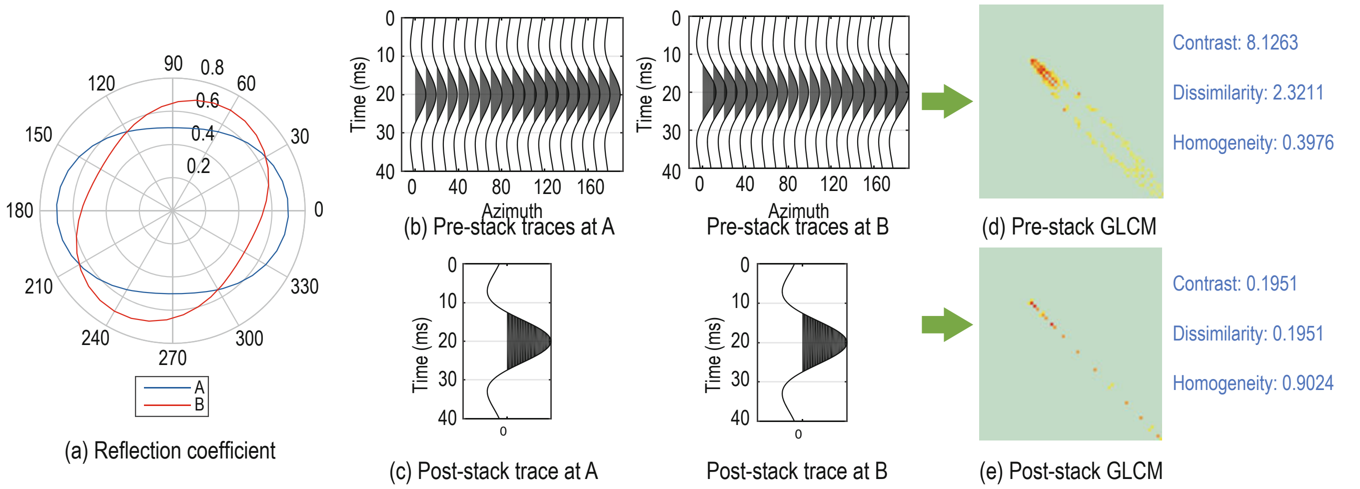
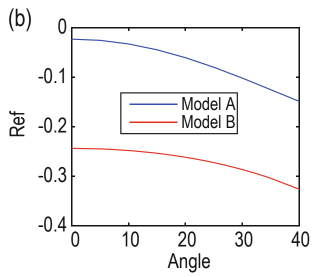



**Fig.5 Texture attributes describing changes in traces of two points.**

Figure 6 shows the synthetic traces of two different AVO characteristics and associated GLCMs. The change degree of the reflection coefficient with an incident angle is different, and its value of “A” is bigger than that of “B.” The GLCMs of two pre-stack gathers from two models are significantly different. Compared with model B, there is a significant degree of deviation from the diagonal of GLCM elements for model A, and it thus has high contrast, high otherness, and low homogeneity.

(a)

| | Lithology | $\alpha$ (m/s) | $\beta$ (m/s) | $\rho$ (g/cm$^3$) |
|---|---|---|---|---|
| Model A | Shale | 2645 | 1170 | 2. 29 |
| | Gasbearing sand | 2780 | 1665 | 2. 08 |
| Model B | Shale | 2190 | 820 | 2. 16 |
| | Gasbearing sand | 1545 | 900 | 1. 88 |



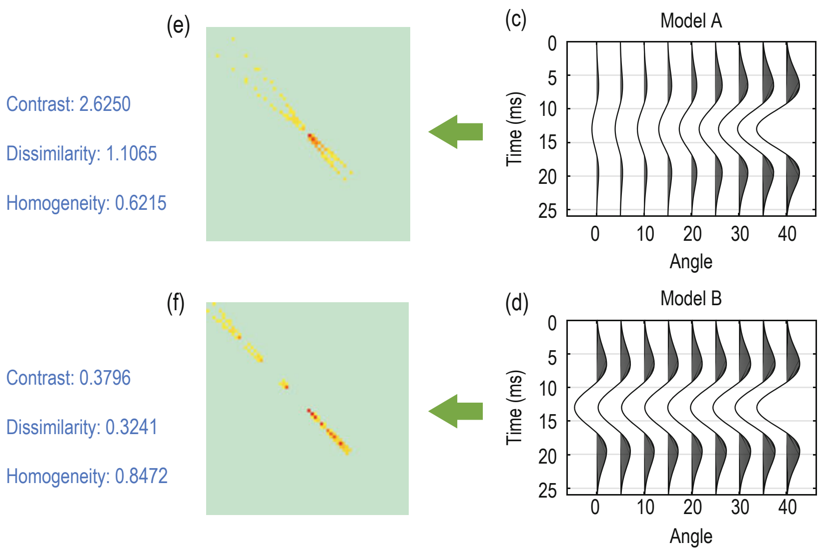




**Fig.6 Texture attributes for two models with different AVO features.**

Figure 7 show the synthetic traces of a wide azimuth and its GLCM feature. Model A does not have anisotropy, while model B has obvious anisotropic characteristics and the reflection coefficient is changed with the azimuth. Thus, the GLCM elements of model A are on the diagonal and those of model B deviate from the diagonal. Model B has higher contrast, higher dissimilarity, and lower homogeneity.

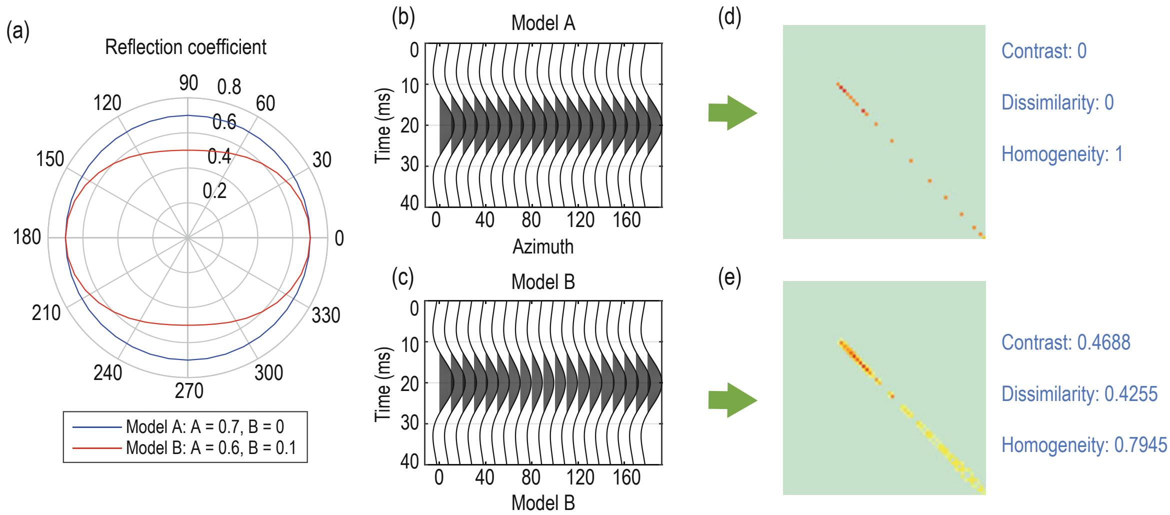



**Fig.7 Texture attributes for two models with and without anisotropic characteristics.**

## Seismic facies analysis using pre-stack texture attributes

In the process of seismic facies analysis, the quality of classification results depends largely on whether the selection of seismic attributes can distinguish different reflection patterns. Many textural properties can be extracted from pre-stack data to describe pre-stack seismic waveform characteristics, and as they give a rich expression of strata features they can be used to effectively distinguish between different pre-stack reflection patterns. In addition, they can assist with analysis of reservoir characteristics in different reflection patterns. The SOM algorithm is widely used in seismic facies analysis (Roy et al., 2010; de Matos et al., 2010; Marroquín et al., 2008). Using a combination of multi-directional pre-stack texture and SOM clustering techniques, we developed the pre-stack-data-based seismic facies analysis method, and the workflow of this method is show in Figure 8.

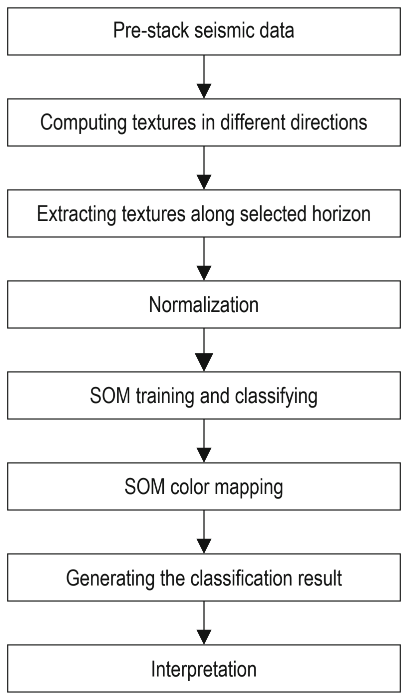



**Fig.8 Workflow of pre-stack-data-based seismic facies analysis using pre-stack texture attributes.**

In this, we first compute the texture attributes in different directions based on pre-stack seismic data. The attributes extracted along the horizon of interest are then input to the SOM clustering process, which generates different pre-stack reflection patterns with features reflected in the model vectors. Principle component analysis is then used to obtain two main projection vectors. The SOM model vectors are then projected into the 2D x-y plane using projection vectors and each classification gives a HSV color value according the following formula (de Matos et al., 2010),

$$Hue = tan^{-1}\left(\frac{y-0.5}{x-0.5}\right), \quad (9)$$

$$Sat = \sqrt{(x-0.5)^2 + (y-0.5)^2}. \quad (10)$$

After color mapping, each classification has a color value and similar colors belong to the same seismic pre-stack reflection pattern. Finally, we are able to analyze the seismic facies using a combination of the classification results, model vectors, well information, and related seismic material.

## Application to field data

We then apply our method to a real seismic data set obtained from the Sichuan Basin in China, to extract the texture attributes and perform seismic facies analysis. The set acquisition was carried out using a wide azimuth measure with a sampling rate of 1 m/s and the dominant frequency of the target zone of about 37 Hz. After testing a variety of parameters we finally decided on the values of Nx = Ny = 5, Nz = 27 for computing the texture attributes in three direction sets, which generate texture attributes between different reflection points where $w \in \{(0,1,0,0),(1,0,0,0),(1,1,0,0),(1,-1,0,0)\}$, texture attributes along time direction where $w \in \{(0,0,1,0)\}$, and texture attributes in the reflection bin where $w \in \{(0,0,0,1)\}$.

Figure 9a shows the contrast attributes of pre-stack textures between different reflection bins. To illustrate the advantages of pre-stack texture attributes, we use the same parameters to extract the contrast attributes from the post-stack seismic data, as shown in Figure 9b. The comparison of two attribute maps demonstrates that improvements can be made using the pre-stack data. Pre-stack texture attributes have more abundant details in area “B” and are more continuous in areas “C” and “D” than the post-stack texture attributes. Along the AA’ line, there are significant differences between the two results, thereby indicating the superiority of pre-stack texture. Overall, the pre-stack texture attributes have the ability to accurately describe geological phenomenon, and the lateral distribution characteristics of the fracture system are much clearer.

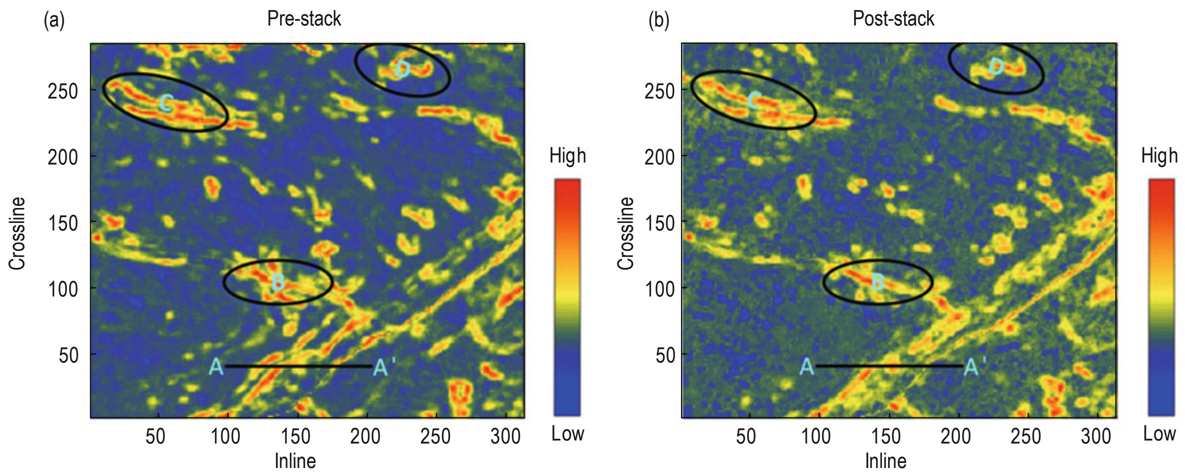



**Fig.9 Contrast attributes of texture between different reflection bins.**

To verify the reasonability of pre-stack texture, we extract the post- and pre-stack data section of different azimuths along the AA’ line, as shown in Figures 10 and 11, respectively. The yellow arrow indicates the location where waveforms have obvious variations. The lateral change in Figure 10 is consistent with Figure 9a. However, the post-stack texture has greater discontinuity with a loss of detail due to the effect of waveform stack.

Figure 12a shows the contrast attributes in the reflection bin, which describe the reservoir characteristics in the area. From Figure 12a, it is evident that point “A” has a higher value than point “B.” Thus, pre-stack traces of point “A” have a relatively great variation with the azimuth. We can speculate that strong anisotropy or strong medium heterogeneity exists at point “A.” In contrast, the value at point “B” is lower, thereby indicating a uniform medium. The pre-stack traces of the two points are shown in Figures 12b and 12c. It is evident that there are larger amplitude differences with different azimuth at point “A,” which is consistent with the inference from pre-stack texture attributes.

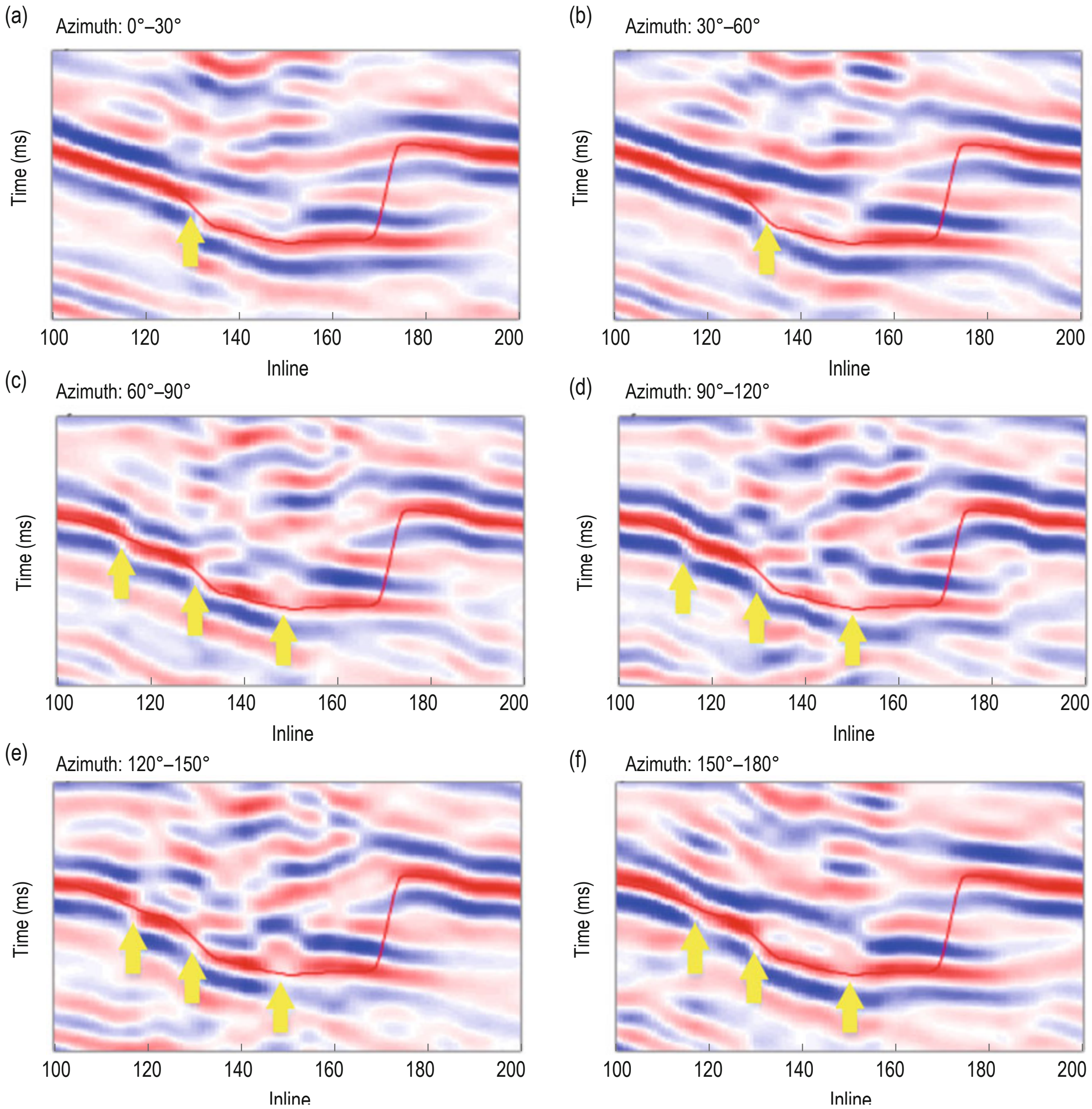



**Fig.10 Seismic data section of different azimuth along AA' line.**

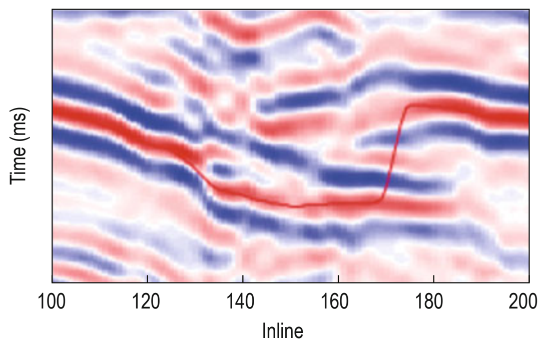



**Fig.11 Post-stack seismic data section along AA' line.**

Seismic analysis can thus be achieved by combining texture properties and the SOM algorithm, as shown in Figure 13a. Figure 13b shows the SOM color code, which indicates that there are four major reflection patterns in the area. The models are shown in Figure 13c, and these are analyzed and summarized as follows:

1. Class 1 has low contrast and high homogeneity along the time direction, which indicates a low reflection coefficient. The contrast in the reflection bin is moderate. Thus, Class 1 has a low amplitude and moderate continuous reflection structure. In addition, the medium of Class 1 could be heterogeneous or rich in fractures due to the relatively higher contrast in the reflection bin.

2. Class 2 has a relatively higher contrast along the time direction and lower contrast in the reflection bin. Thus, Class 2 has a moderate amplitude and continuous reflection structure. The medium of Class 2 could be uniform due to the low contrast in the reflection bin.

3. Class 3 has a higher contrast along the time

direction and a lower value among the reflection bins. Thus, Class 3 has a high amplitude and continuous reflection structure. The medium of Class 3 could thus be uniform, which is similar to Class 2.

4. Class 4 is similar to Class 1 in terms of the reflection coefficient, but it has a higher contrast between different reflection bins. Thus, Class 4 has a low amplitude and a discontinuous reflection structure. The medium of Class 4 could be heterogeneous or contain fractures of a lower degree than Class 1.

A further and more accurate interpretation of the sedimentary environment and reservoir characteristics can be made using well information and related material.

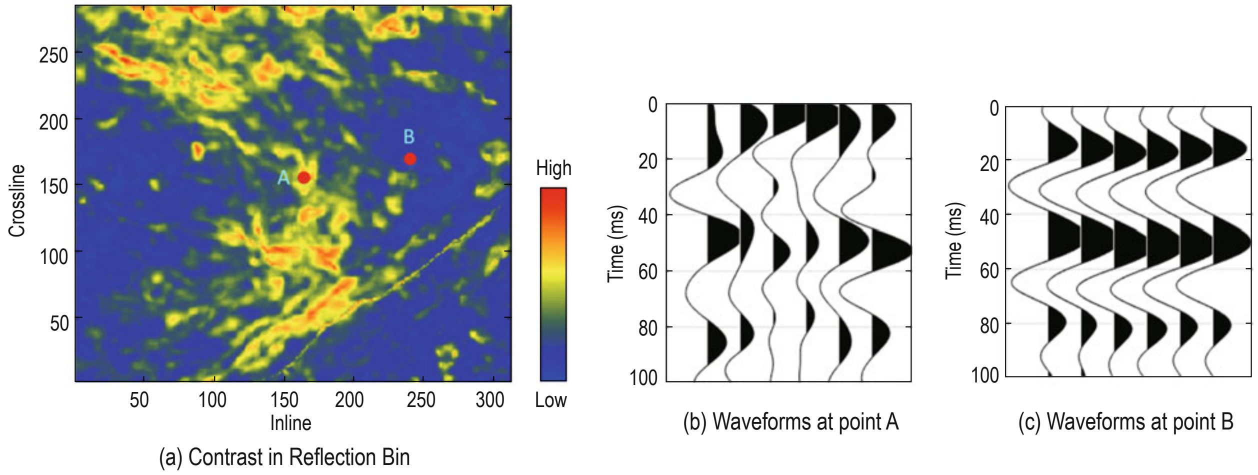



**Fig.12 Texture attributes in reflection bin.**

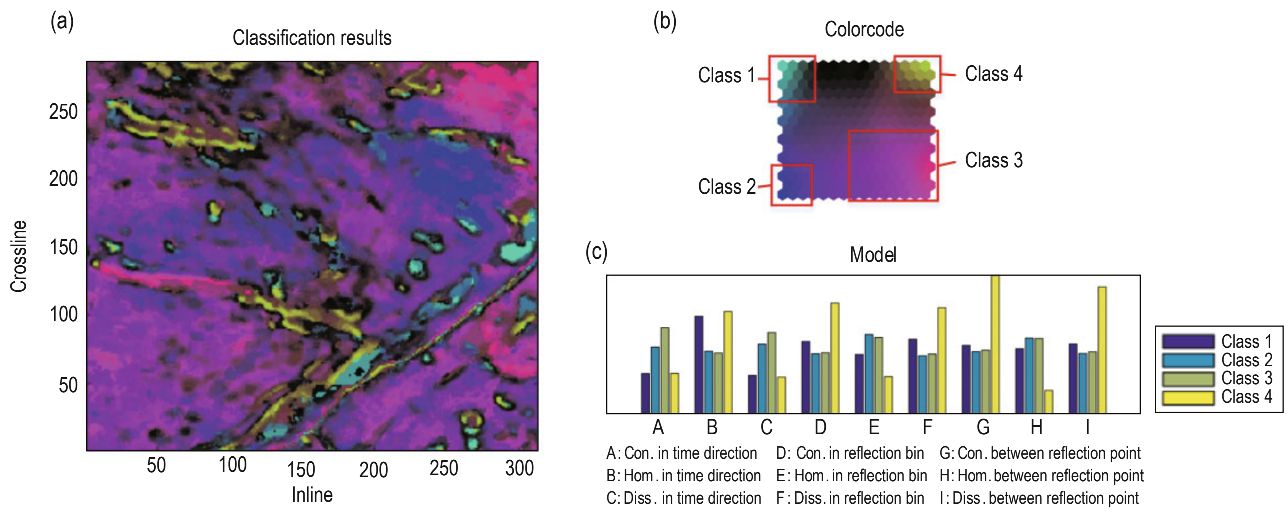



**Fig.13 Texture classification results and model vector.**

## Conclusions

This paper proposes a method for extracting pre-stack seismic texture attributes based on pre-stack seismic data, which can then be used for seismic facies analysis when combined using a clustering algorithm. Compared with traditional texture attributes, pre-stack texture attributes have the ability to describe more subtle lateral changes and can be used for reservoir characters analysis. The pre-stack-texture-based seismic facies analysis technique synthetically utilizes the amplitude variation features between different reflection points in pre-stack trace gathers obtained from a common reflection bin and in the time direction. It can also reveal different pre-stack reflection patterns and assist in locating complex or fractured reservoirs; it therefore has considerable research value.

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