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Geological Structure Interpretation of Coalbed Methane Enrichment Area based on VMDC and Curvature Attributes

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Abstract: Geological structures play a leading role in the occurrence characteristics of coalbed methane (CBM), and curvature attributes are an important geometric seismic attribute that can be used to identify a geological structure. In view of the characteristics of curvature attributes which are easily affected by noise, this paper proposes a method based on variational mode decomposition and correlation coefficients (VMDC) for denoising, and then extracts curvature attributes for geological structure interpretation. The geological models with anticline, syncline and normal fault structure characteristics are constructed, and curvature attributes of geological models without noise and with different percentages of random noise are calculated respectively. According to the time window test results, the 5×5 time window is more suitable in the case of no noise, while 9×9 time window is more suitable when there is noise. The results also show that both the median filtering and VMDC can suppress random noise, but VMDC can suppress noise better and improve the accuracy of curvature attributes. Mean curvature attributes can effectively identify geological structures such as anticlines, synclines and faults. Gauss curvature is not ideal for identifying geological structures. Both the maximum positive curvature and the minimum negative curvature have obvious responses to some geological structures. The method has been applied to a CBM enrichment area prediction in Qinshui Basin, China, and the geological structure characteristics of this area have been preliminarily interpreted. The known CBM content information verifies the feasibility and effectiveness of the proposed method.

Keywords: curvature attribute; geological structures; interpretation; CBM; VMDC

1. Introduction

Coalbed methane (CBM) is one type of coal associated natural gases in coal seams with the methane as the main component. It belongs to the self-generated and self-reservoir unconventional gas [1–3]. Geological structures play a leading role in the occurrence characteristics of CBM enrichment area [4,5], and the development of the fracture system could improve the fracture ratio of the coal seam. However, too much fracture development may cause CBM emission and make it hard to store. Therefore, the implementation of structural interpretation in a CBM enrichment area has important guiding and practical significance for understanding the characteristics of CBM reservoir structures and CBM exploration and development.

Curvature attribute is a method of structural interpretation using the degree of curvature of seismic reflection data. It could effectively indicate the transverse fluctuations and interruption due to

strata bending, folds, cracks, faults and so on [6–8]. In recent years, curvature attribute has achieved rapid development and application. Lisle [9] proposed a method of high strain anomaly area predicted by the Gauss curvature and demonstrated the correlation of fracture densities and Gaussian curvature. Roberts [10] introduced the calculation formula and the physical meaning of curvature attributes, and the detailed steps for calculating curvature attributes were provided. Sigismondi et al. [11] introduced the curvature application of Argentina basins. Marroqun et al. [12] detected the subtle structural features of CBM reservoirs based on the curvature attributes derived from seismic horizons. Al-Dossary et al. [13] proposed the volumetric spectral estimates of reflector curvature. Blumentritt et al. [14] provided a method to illuminate fracture orientations based on the volume curvature attributes. Chopra et al. [6–8] used the curvature attributes to 3D surface seismic data and pointed out that the volume attributes are powerful tools which can be used to predict the fractures and other stratigraphic features. Hunt et al. [15] quantitatively estimated the fracture density variations based on the azimuthal amplitude variation with offset (AVO) and curvature attributes. The basic theory and application effect of curvature attributes are discussed in Mai's doctoral dissertation [16]. Chehrazai et al. [17] used the seismic attributes, such as curvature, coherency and similarity to predict the fault based on neural networks. Chopra et al. [18] compared structural curvature and amplitude curvature, and found that the amplitude curvature had better resolution. Gao [19] proposed a new curvature gradient algorithm and demonstrated its application. Qi et al. [20] found that the Karst area has the following characteristics: strong dip, negative curvature, low coherence, and a shift to lower frequencies. Yu [21] prepared a cylindrical surface-based curvature algorithm as an aid to delineate faults and fractures. Di et al. [22–25] proposed a new algorithm for volumetric curvature and flexure, which can improve the fracture detection. Liao et al. [25] used coherence, dip azimuth, and curvature to delineate fault damage zone. Ha et al. [26] delineated subtle geologic features in the seismic data based on the most-positive and most-negative curvature. Hunt et al. [27] focused on the window size and filtering methods for seismic curvature estimates. Karbalaali et al. [28] pointed out that the positive curvature attribute can clearly image channel levies, and the negative curvature can clearly image channel centers. The above methods mainly focus on the curvature attribute algorithm and its application. However, the research on curvature attributes time window and the relationship between different curvature attributes and geological structures is still limited.

The main methods of denoising in seismic exploration are the median filter method, f - x prediction filter method, polynomial fitting method, wavelet transform, and empirical mode decomposition (EMD) method [29–34]. Variational mode decomposition (VMD) is an adaptive signal processing method. Huang et al. [35] developed a method for seismic data random noise attenuation based on VMD and correlation coefficients. Their research shows that this method has a strong ability for random noise attenuation.

In this paper, the influence of the time window on curvature attributes and the relationship between different curvature attributes and geological structures are studied by constructing geological models with anticlines, synclines and normal faults. In view of the characteristics of curvature attributes which are easy to be affected by noise, this paper also proposes a denoising method of seismic data based on variational mode decomposition and correlation coefficients (VMDC) and then extracts curvature attributes for geological structure interpretation. Finally, this method is applied to the prediction of the coalbed methane enrichment area.

2. Basic Theory

2.1. Curvature Attributes

The common calculation methods of curvature attributes are the curvature analysis method based on surface fitting, the conventional Fourier transform method, and the maximum principal curvature method [16–18]. Among them, the curvature calculation method based on surface fitting is the most widely used [16]. Considering the 3×3 difference grid in Figure 1 as an example, $Z_1, Z_2, \dots, Z_9$

represent the horizon time values; the calculation methods for various curvature attributes are also presented [10].

Figure 1. 3×3 grid cell [10].

This method is used to calculate the derivatives by the difference; after grid computing of seismic data interpretation, the curvature at point Z_5 could be calculated by least squares fitting for the local quadric surface by using the surrounding eight grid points, that is Z_1 to Z_9 , except Z_5 . The obtained structure surface could be expressed by the quadratic equation in formula (1), as follows:

$$Z(x, y) = ax^2 + by^2 + cxy + dx + ey + f \quad (1)$$

Then a 3×3 grid cell is applied; after introducing the difference approximation to the derivatives, the calculation of coefficients in formula (1) could be simplified as a series of simple expressions, as follows; the expressions for calculating coefficients are provided in Ref. [10].

$$a = \frac{dz^2}{2dx^2} = \frac{z_1 + z_3 + z_4 + z_6 + z_7 + z_9}{12\Delta x^2} - \frac{z_2 + z_5 + z_8}{6\Delta x^2} \quad (2)$$

$$b = \frac{d^2z}{2dy^2} = \frac{z_1 + z_2 + z_3 + z_7 + z_8 + z_9}{12\Delta x^2} - \frac{z_4 + z_5 + z_6}{6\Delta x^2} \quad (3)$$

$$c = \frac{d^2z}{2dxdy} = \frac{z_3 + z_7 - z_9}{4\Delta x^2} \quad (4)$$

$$d = \frac{dz}{dx} = \frac{z_3 + z_6 + z_9 - z_1 - z_4 - z_7}{6\Delta x^2} \quad (5)$$

$$e = \frac{dz}{dy} = \frac{z_1 + z_2 + z_3 - z_7 - z_8 - z_9}{6\Delta x^2} \quad (6)$$

$$f = \frac{2(z_1 + z_4 + z_6 + z_8) - (z_1 + z_3 + z_7 + z_9) + 5z_5}{9} \quad (7)$$

Where $z_1 - z_9$ are the values of grid points of No.1–9 as illustrated in Figure 1, and Δx is the distance between grid points. Then the calculation formulas of various curvature attributes can be obtained by the above coefficients.

1) Mean curvature

The mean curvature is an important characteristic of the surface and could be used to evaluate surface discontinuities and is defined as follows [10]:

$$k_m = \frac{a(1 + e^2) + b(1 + d^2) - cde}{(1 + d^2 + e^2)^{\frac{3}{2}}} \quad (8)$$

2) Gaussian curvature

The Gaussian curvature could reflect the bending, folds, deformations and fractures during the ground settlement process. Generally, the larger the Gaussian curvature, the better the formation permeability. The Gaussian curvature is defined as follows [10]:

$$k_g = \frac{4ab - c^2}{(1 + d^2 + e^2)^2} \quad (9)$$

3) Maximum positive curvature

The maximum positive curvature could magnify the surface's fault information, some small linear structures, and even the footprints due to the interval of the interpretation. The maximum positive curvature is defined as follows [10]:

$$k_{pos} = (a + b) + \sqrt{(a - b)^2 + c^2} \quad (10)$$

4) Minimum negative curvature

The functions of the minimum negative curvature are like the maximum positive curvature. Their combination could be utilized to study the characteristics of the surface discontinuities. The minimum negative curvature is defined as follows [10]:

$$k_{neg} = (a + b) - \sqrt{(a - b)^2 + c^2} \quad (11)$$

2.2. Variational Mode Decomposition and Correlation Coefficients (VMDC)

Curvature attributes are susceptible to noise, and preprocessing of horizon data can effectively improve the accuracy of curvature attributes. VMDC is an effective noise denoising method; the core idea of this method is combining VMD with correlation coefficients [35]. The specific algorithm flow of VMDC can be found in Ref. [35]. Flow chart of curvature attributes extraction based on VMDC is shown in Figure 2. Firstly, VMD was used to decompose the original horizon curve into intrinsic mode functions (IMFs) with different characteristics. Then, the correlation coefficients between each IMF component and the original horizon curve were calculated. The corresponding treatment was carried out based on differences among correlation coefficients of effective signals, random noise and the original horizon curve; the effective horizon curve was also reconstructed. Finally, the curvature attributes were extracted based on the reconstructed horizon curve.

Figure 2. Flow chart of curvature attributes extraction based on VMDC.

3. Theoretical Model Test

3.1. Geological Structure Model

On flat or planar dipping surfaces, the curvature is zero; on the anticlines, the curvature is defined as positive; and on the synclines, the curvature is defined as negative [10]. Based on the above understanding, we constructed a geological model with syncline, anticline and normal fault, as shown in Figure 3. In this model, a syncline is set at Inline 100-Inline 200, an anticline is set at Inline 300-Inline 400, and a fault is set at Inline 500-Inline 600; other locations are horizontal layers.

Figure 3. Geological structure model.

3.2. Time window test of Curvature Attribute

The mean curvature is an important characteristic of the surface and could be used to evaluate surface discontinuities [10]. We take the mean curvature attribute as an example to discuss the influence of different percentages of noise and different time windows on the curvature attributes.

It can be seen from Figure 4 and Table 1 that mean curvature attributes calculated at different time windows are strongly correlated with horizon curves without noise. When the time window is 3×3 , the correlation coefficient is 0.59, and the mean curvature is not sensitive to the response of faults in this time window. When the time window is 5×5 , the correlation coefficient reaches 0.61. The mean curvature calculated by this window has a good response to anticlines, synclines and normal faults. In the case of no noise, the correlation coefficient remains basically the same as the time window increases. Therefore, in order to depict the geological structure, the time window of 5×5 is more appropriate in this case of no noise.

Table 1. Correlation coefficient for different time windows without noise.

Time Window Size	3×3	5×5	7×7	9×9	11×11
Correlation coefficient	0.59	0.61	0.61	0.61	0.60

In order to analyze the influence of different time windows on noise in curvature attributes, 2%, 5%, 10%, and 20% Gaussian random noise is added to the horizon curve. In the case of different signal-to-noise ratios, as shown in Figures 5–8, the mean curvature attributes obtained by different time windows are the same color as those in Figure 4. As shown in Figure 5, although there is only 2% random noise, it has a great influence on the mean curvature. When the time window is 3×3 , the correlation coefficient is only 0.44. It can be seen from Table 2, when the time window is 9×9 , the correlation coefficient reaches 0.45. Compared with no noise, the correlation coefficient has been significantly reduced.

Figure 4. Horizon curve and mean curvature attribute without noise: (a) Horizon curve and (b) mean curvature attribute of different time windows without noise.

Figure 5. Horizon curve and mean curvature attribute with 2% noise: (a) Horizon curve and (b) mean curvature attribute of different time windows with 2% noise.

Table 2. Correlation coefficient for different time windows with 2% noise.

Time Window Size	3 × 3	5 × 5	7 × 7	9 × 9	11 × 11
Correlation coefficient	0.44	0.42	0.41	0.45	0.43

It can be seen from Figure 6 and Table 3, when the noise is 5%, the correlation coefficient has a tendency to decrease. When the time window is 3 × 3, the correlation coefficient is only 0.43. When the time window is 9 × 9, the correlation coefficient reaches 0.44. Due to the influence of noise, the calculation of large time windows is basically the same.

Figure 6. Horizon curve and mean curvature attribute with 5% noise: (a) Horizon curve and (b) mean curvature attribute of different time windows with 5% noise.

Figure 7. Horizon curve and mean curvature attribute with 10% noise: (a) Horizon curve and (b) mean curvature attribute of different time windows with 10% noise.

Table 3. Correlation coefficient for different time windows with 5% noise.

Time Window Size	3×3	5×5	7×7	9×9	11×11
Correlation coefficient	0.43	0.42	0.41	0.44	0.42

It can be seen from Figure 7 and Table 4 that the correlation coefficients are significantly reduced when there is 10% random noise. The correlation coefficient is the largest when using the time window of 5×5 , but it is only 0.43.

It can be seen from Figure 8 and Table 5, when the noise is 20%, the correlation coefficient decreases obviously and its maximum value is only 0.42. The mean curvature value basically does not reflect the characteristics of geological structures.

Figure 8. Horizon curve and mean curvature attribute with 20% noise: (a) Horizon curve and (b) mean curvature attribute of different time windows with 20% noise.

Table 4. Correlation coefficient for different time windows with 10% noise.

Time Window Size	3 × 3	5 × 5	7 × 7	9 × 9	11 × 11
Correlation coefficient	0.42	0.43	0.40	0.40	0.40

Table 5. Correlation coefficient for different time windows with 20% noise.

Time Window Size	3 × 3	5 × 5	7 × 7	9 × 9	11 × 11
Correlation coefficient	0.41	0.42	0.40	0.40	0.38

Therefore, noise has a great influence on the mean curvature attributes, and a smaller noise can cause larger errors. The smaller time window reflects the detailed features of the geological structure, while the larger time window reflects the overall shape of the geological structure.

In order to overcome the influence of random noise on curvature attributes, the random noise in the horizon curve is suppressed by the method of median filter and VMDC. In Figure 9a, the blue curve is the horizon curve without noise, and the red curve is a curve reconstructed by a median filter. In Figure 10a, the red curve is a curve reconstructed by VMDC. Comparing Figures 9 and 10, it can be seen that both the median filtering and VMDC can suppress random noise, but VMDC can suppress noise better.

It can be seen from Figure 9 and Table 6 that the correlation coefficient of curvature attributes decreases first and then increases with the increase of the time window after denoising with the median filter. Comparing Tables 1, 4 and 6, we can see that after the median filtering process, the correlation coefficient of the curvature attribute value has been improved, but it is different from that without noise. When the time window of 9 × 9 is used, the correlation coefficient is the largest, but it is only 0.45. It is much lower than 0.61 in the case of no noise.

Table 6. Correlation coefficient for different time windows after denoising based on median filter.

Time Window Size	3 × 3	5 × 5	7 × 7	9 × 9	11 × 11
Correlation coefficient	0.43	0.42	0.41	0.45	0.40

Figure 9. Horizon curve and curvature attributes: (a) Reconstruction results of horizon curve by median filter and (b) curvature attributes of different time windows after denoising based on median filter.

Figure 10. Horizon curve and curvature attributes: (a) Reconstruction results of horizon curve by VMDC and (b) curvature attributes of different time windows after denoising based on VMDC.

It can be seen from Figure 10 and Table 7 that the correlation coefficients of the curvature attributes after denoising with VMDC are obviously improved. When the time window size of 9×9 is used, the correlation coefficient is up to 0.53. The VMDC method can effectively reduce the influence of random noise. Therefore, in order to depict the geological structure, the time window of 9×9 is more appropriate.

Table 7. Correlation coefficient for different time windows after denoising based on VMDC.

Time Window Size	3×3	5×5	7×7	9×9	11×11
Correlation coefficient	0.51	0.47	0.46	0.53	0.42

In summary, mean curvature attribute is more susceptible to noise, and the sensitivity of different time windows to curvature attributes is different; both the median filtering and VMDC can suppress

random noise, but VMDC can suppress noise better and improve the accuracy of calculation of curvature attributes. The 5×5 time window is more suitable in the case of no noise, while the 9×9 time window is more suitable when there is noise.

3.3. Response of Curvature Attributes to Geological Structural

According to the time window test of curvature attributes, we can see that the different time windows have different effects on curvature calculation results. This section discusses and analyzes the differences in the results of the curvature attributes before and after de-noising. Therefore, when we calculate the curvature attributes, we all choose the same window size, which is 9×9 .

In order to analyze the geological structure corresponding to the curvature attributes, curvature attributes of geological models without noise and with 10% Gauss random noise are calculated respectively. We also know that on flat or planar dipping surfaces, the curvature is zero; on the anticlines, the curvature is defined as positive; and on the synclines, the curvature is defined as negative [10]. Based on the above understanding, we analyze the curvature attributes. It can be seen from Figure 11 that the mean curvature attribute responds to geological structures such as synclines, anticlines and faults. The mean curvature value is negative in synclines and on the hanging wall of faults, and positive in anticlines and on the foot wall of faults; the shape of the mean curvature value is basically the same as that of the geological structure. Gauss curvature also responds to synclines, anticlines and faults, but the curvature value is positive, so it is impossible to distinguish specific geological structures by Gauss curvature value. The maximum positive curvature is sensitive to the anticlines and the foot wall of faults, and the curvature value is positive, however, the value is insensitive to the synclines and the hanging wall of the faults. Minimum negative curvature is sensitive to syncline and the hanging wall of the fault, and the curvature value is negative, but the value is insensitive to anticline and the foot wall of the faults.

Figure 11. Horizon curve and curvature attributes without noise: (a) Horizon curve and (b) curvature attributes without noise.

Figure 12 is the horizon curve and curvature attributes with 10% Gauss random noise. It can be seen that due to the influence of random noise, each curvature attribute is disturbed, and the ability to reflect the characteristics of geological structures is also affected. Among them, the mean curvature has a large variation range, but the curvature value also is negative in synclines and positive in anticlines; positive in the foot wall and negative in the hanging wall of faults, and the shape of the curvature value is also basically the same as that of the geological structure. The change of Gauss curvature

value is rather violent and cannot effectively reflect the characteristics of geological structure. The maximum positive curvature and the minimum negative curvature are also disturbed by noise, and the characterization of geological structural features is affected.

Figure 12. Horizon curve and curvature attributes with 10% noise: (a) Horizon curve and (b) curvature attributes with 10% noise.

In order to overcome the influence of random noise on curvature attributes, the random noise of the horizon data is suppressed by the method of median filter and VMDC. In Figure 13a, the blue curve is the horizon curve without noise, and the red curve is a curve reconstructed by a median filter. In Figure 14a, the red curve is a curve reconstructed by VMDC. Compared Figures 13 and 14, it can be seen that both the median filtering and VMDC can suppress random noise, but VMDC can suppress noise better. Curvature attributes after denoising also illustrate the above conclusions. Although the correlation between curvature attributes and geological structures in Figure 13 has been improved, the results are still not satisfactory because curvature attributes are sensitive to noise. In Figure 14, compared with the response characteristics of the geological structure before noise suppression, the mean curvature attribute has been improved obviously, and its change morphology is basically consistent with the geological structure. The response effect of Gauss curvature has also been improved, but the specific geological structure cannot be distinguished by Gauss curvature. The sensitivity of the maximum positive curvature and minimum negative curvature to the response characteristics of geological structures has been enhanced, and both curvature attributes have an obvious response to some geological structures.

In summary, among several curvature attributes, the mean curvature attributes can effectively reveal the characteristics of geological structures, and the structure of geological structures can be judged by curvature attribute values. Gaussian curvature responds to all geologic structures, but its curvature values are positive. It is not possible to distinguish specific geological structures by Gaussian curvature values. Both the maximum positive curvature and the minimum negative curvature are obviously responsive to some geological structures, but they are also insensitive to some geological structures. Therefore, it is necessary to carry out VMDC denoising pre-processing before using curvature attributes to study geological structures.

Figure 13. Horizon curve and curvature attributes: (a) Reconstruction results of horizon curve by median filter and (b) curvature attributes after denoising based on median filter.

Figure 14. Horizon curve and curvature attributes: (a) Reconstruction results of horizon curve by VMDC and (b) curvature attributes after denoising based on VMDC.

4. Case Study

The research area is located in a mining area southeast of China's Shanxi province. The coal seams to have wide distribution, large thickness and high CBM content. There are abundant CBM resources. Therefore, the structural interpretation based on curvature attributes is conducive to exploration, development of CBM resources, optimization of energy the structure, and protection of ecological protection [36].

This research selects No.3# coal seam as the research object. As one of the relatively stable and minable seams, the No.3# coal seam is located in the Lower Permian Shanxi (P1s) in this region. Its thickness is between 6.49m and 7.45m with an average of 6.79m [37,38]. Its roof and floor is mainly composed of mudstone and sandy mudstone. There are seven CBM wells whose specific positions and CBM content are shown in Table 8.

Table 8. CBM drilling information of this exploration area.

Well Number	Inline	Xline	CBM Content (m ³ /t)
Well-1	97	83	10.12
Well-2	63	182	8.68
Well-3	218	93	12.51
Well-4	24	322	17.58
Well-5	87	306	18.02
Well-6	202	318	16.85
Well-7	190	420	9.79

The main fault development is a monoclinial structure advancing NNE and striking NWW [38]. On this basis, a secondary wide and gentle fold develops, and the rock (coal) seam undulation can be found. The strata inclination is generally no more than 10°, and local inclination can reach 17°. Small faults are well developed along with the karstic collapse structures, but not on a massive scale. The occurrence of CBM in this area has obvious regularity. The CBM enrichment area is at syncline axis with high CBM content, while the CBM non-enrichment area is at anticline axis with a relatively low CBM content [39].

Figure 15 is the reconstruction horizon time of 3# coal seam based on VMDC. It can be seen from the figure that the horizon in this area has a tendency to be higher in the west and lower in the east, and has obvious regional zoning characteristics.

Figure 15. Reconstruction Horizon time of 3# coal seam based on VMDC.

The three curvature attributes, i.e., the mean curvature, maximum positive curvature and minimum negative curvature are extracted along the 3# coal seam horizons. The results are shown in Figures 16–18.

Figure 16 shows the mean curvature attribute of 3# coal seam. It mainly has a positive value in the east and west regions. Combined with the conclusion that the mean curvature value is negative in synclines and the hanging wall of faults, and positive in anticlines and the foot wall of faults, the area where the positive curvature is located mainly develops anticlines and the foot wall of faults, which is not conducive to CBM enrichment. The mean curvature is mainly negative in the central oval region; the syncline structures mainly develop and the hanging wall of fault development, which is conducive to CBM enrichment. According to the CBM value of drilling information in this exploration area, three CBM wells with relatively high CBM content are all in the syncline structure areas, and the degree of fault development is in general level. In addition, four CBM wells with low and medium

CBM content are in the anticline structure area and the faults are well developed. Therefore, the mean curvature-based anticline, syncline and fault interpretation are basically consistent with the CBM content in this region.

Figure 16. Mean curvature of 3# coal seam.

Figure 17 shows the maximum positive curvature attribute. It mainly has a positive curvature value in the east and west regions. Combined with the conclusion that the maximum positive curvature is sensitive to the anticlines, the foot wall of faults and the curvature value is positive; this area mainly develops anticline and the foot wall of faults structure. The faults are developed well with higher resolution than mean curvature. The CBM contents of the CBM wells are at the low and medium level. This is consistent with the geological law that the CBM non-enrichment area is at the anticline axis and the fault development is not conducive to CBM enrichment.

Figure 17. Most positive curvature of 3# coal seam.

Figure 18 shows the minimum negative curvature attribute. Combining with the conclusion that the minimum negative curvature is sensitive to syncline and the hanging wall of fault, and the curvature value is negative. It mainly has a negative curvature value in the central oval region. The syncline structures mainly develop and the hanging wall of fault development is in general. The CBM

contents of the three CBM wells are relatively high in this region. This is consistent with the geological law that the CBM enrichment area is at the anticline axis and the fault development in general level is conducive to CBM enrichment.

Figure 18. Negative curvatures curvature of 3# coal seam.

Above the comprehensive analysis of mean curvature, maximum positive curvature and minimum negative curvature, the anticline structures mainly develop in the east and west regions and faults are developed well, which is not conducive to CBM enrichment. The syncline structures mainly develop in the central oval region and the degree of fault development is in general, which is conducive to CBM enrichment.

5. Conclusions

In view of the characteristics of curvature attributes which are easily affected by noise, this paper proposes a denoising method of seismic data based on VMDC and then extracts curvature attributes for geological structure interpretation. This paper has obtained the following conclusions:

- 1) Curvature attributes are easily affected by noise and both the median filtering and VMDC can suppress random noise, but VMDC can suppress noise better and improve the accuracy of calculation of curvature attributes.
- 2) According to the time window test results, the 5×5 time window is more suitable in the case of no noise, while the 9×9 time window is more suitable when there is noise.
- 3) The mean curvature value is negative in synclines and on the hanging wall of faults, and positive in anticlines and on the foot wall of faults. Gauss curvature is impossible to distinguish for specific geological structures. The maximum positive curvature is sensitive to the anticlines and the foot wall of faults. The Minimum negative curvature is sensitive to synclines and the hanging wall of fault.
- 4) The actual application results indicate that we can use curvature attributes to interpret the geological structure and then predict the CBM enrichment based on the structure. Moreover, the results of the structural interpretation have important guiding values for CBM exploration and development.

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