PRESTACK SEISMIC INVERSION BASED ON ADAPTIVE MIXED-NORM CONSTRAINTS

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ABSTRACT

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Prior information plays a critical role in seismic inversion, which is used to reduce the ill-posed problem. Most of the inversion methods assume that the noise obeys Gaussian distribution. However, due to the diversity of noise in seismic data, it can hardly meet the prior hypothesis. In this paper, a seismic prestack inversion method based on adaptive mixed-norm constraint is proposed to cope with the different noise distribution, and improve the noise suppressing ability of inversion algorithm in prestack seismic data. First, the noise analysis of actual shale gas is realized through the forward modeling of well logging data. Second, the constraints of the L_2 norm and the L_4 norm are added to the target function. The new algorithm combines the ability of L_2 norm on super-Gaussian and Gaussian noise, and L_4 norm on sub-Gaussian noise. It adaptively regulates the weights between L_2 norm and L_4 norm through Kurtosis. This method improves the adaptive ability of the algorithm to sub-Gaussian, Gaussian, and super-Gaussian noise. By identifying the types of noise, the adaptive mix-norm inversion method is used to test the model, and the prestack simultaneous inversion is carried out in the actual shale gas data. The results show that the proposed method can obtain better inversion results compared to conventional methods.

KEY WORDS: prestack inversion, mixed-norm, noise suppressing, Kurtosis.

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INTRODUCTION

Prestack seismic inversion can obtain elastic parameters of subsurface medium by utilizing seismic data and drilling data, such as shear wave velocity, shear wave velocity ratio, Poisson ratio, and Lamé coefficient, etc. The changes of these data are used to predict the subsurface lithology, physical property, and gas-bearing properties, etc. However, due to the influence of frequency bandwidth and noise, prestack inversion is usually difficult to obtain stable and unique results, and usually requires prior information to restrain the inversion process.

Prior information is widely distributed, some of which are used to reduce the ill-posed nature of inversion, some of which depend on geologists' prior knowledge, and some are aimed at improving the suppressing effect of inversion algorithm on seismic data noise (Alemie and Sacchi, 2011; Yuan, 2017). According to different objects, it can be divided into the priori information on the parameters and noise, respectively. Usually, these two ways will be applied simultaneously.

Buland and Omre (2003) put forward a prestack inversion method based on Bayesian framework, which add the priori hypothesis into the inversion process, and assume the elastic parameters accord with the characteristics of Gaussian distribution. To some extent, this method improved the stability of the inversion process. On the basis of this study, Downton (2005) considers that the resolution of Cauchy distribution is better than that of Gaussian distribution. Chen and Yin (2007) published a method on prestack inversion under the Bayesian framework, which improves the stability of the inversion by the covariance matrix. Chen et al. (2007) also point out that the result of Huber prior distribution is better than the Gaussian prior distribution under the condition of noise. Alemie and Sacchi (2011) have studied the inverse problem of multivariable joint Cauchy hypothesis. Theune et al. (2010) compared the effect of the parameters prior information on the inversion results when assuming Gaussian, Cauchy and Laplace distribution respectively, and pointed out that the non-Gaussian distribution can better identify the thin layer and protect formation boundary, and also indicated that the Laplace distribution of inversion results is more stable than Cauchy. Yuan et al. (2012, 2013, 2017) proposed a novel stochastic noise removal method. Based on the idea of inversion, the random noise attenuation method for edge protection was studied in Bayesian framework by using the noise-free signal as the parameter to be inverted, Cauchy distribution as a priori distribution, which has achieved good results. Saraswat and Sen (2012) used a prior probability density function based on the subdivision model to obtain a very high resolution elastic model to constrain the prestack inversion. Velis (2005) used the characteristics of the spatial continuity of the Markov random field as a constraint to invert the seismic data. Tian et al. (2013, 2013b) and Wang et al. (2015) used Markov random fields as the constrained priori information parameters to finally obtain the inversion results with clear boundary changes, high resolution in the vertical direction and reasonable continuity in the horizontal direction.

All the above studies assume that the noise is Gaussian distribution, and the main research direction is on the discussion of the types of parameter distribution. But in fact, the noise distribution is very complicated (Chen et al., 2016**a,b,c ???;** Chen et al., 2017; Chen and Chen, 2017; Chen and Chen et al., 2017; Chen and Zhou et al., 2017; Chen and Fomel, 2017), the Gaussian distribution cannot describe all the features of the noise. Especially for prestack data with low signal-to-noise ratio, the type of noise should be a superposition of multiple distributions (Chen and Ma et al., 2017; Chen and Huang et al. 2017; Mohammad et al. 2017; Xie et al. 2017). Based on the Buland (2003) study, Karimi et al. (2010) discussed the distribution of seismic noise and developed a Bayesian AVO inversion based on closed-skew Gaussian distribution. Liu et al. (2012) and Li et al. (2015) discussed the prestack three-parameter non-Gaussian inversion method based on the L_1 and L_2 mixed-norm. However, due to the non-differentiability of L_1 norm, the Powell algorithm is needed to solve the equation.

In this paper, an adaptive prestack seismic inversion method with mixed-norm constraints is proposed to suppress the prestack seismic data noise and improve the validity of the inversion results. The traditional L_2 norm has good performance under the conditions of Gaussian and super-Gaussian environments. But the inversion algorithm based on L_4 norm has better performance in sub-Gaussian environment. In this paper, by analyzing the seismic data noise type of the actual shale gas, the forward modeling is carried out based on the logging data. Based on the identification of noise types, this paper uses the Fatti equation as the inversion equation, and adds the Gaussian and Laplace distribution noise to the forward seismic data to test inversion results. Finally, the prestack simultaneous inversion in the actual shale gas work area verifies the feasibility of the inversion method and the noise suppression effect.

Prestack simultaneous inversion

Prestack simultaneous inversion is based on the equation proposed by Zoeppritz (1919), which accurately reflects the relationship between amplitude changing with angle of incidence and physical parameters at the interface location. However, due to the complexity of the mathematical relationship between the parameters, it has not been given due attention for a long time since it was proposed. Therefore, the approximate equation of the Zoeppritz equation is most commonly used for simultaneous prestack inversion. Our study is based on the approximate equation proposed by Fatti et al. (1994):

$$\mathrm{R}(\alpha) \approx \frac{1}{2}\left(1+\tan^2\alpha\right)\frac{\Delta \mathrm{I_P}}{\mathrm{I_P}} - 4\left(\frac{v_\mathrm{S}}{v_\mathrm{P}}\right)^2 \frac{\Delta \mathrm{I_P}}{\mathrm{I_P}}\sin^2\alpha + \frac{1}{2}\left[4\left(\frac{v_\mathrm{S}}{v_\mathrm{P}}\right)^2 \sin^2\alpha - \tan^2\alpha\right]\frac{\Delta\rho}{\rho} \quad (1)$$

where I_p is the longitudinal wave impedance, I_S is the shear wave impedance, $\frac{\Delta I_p}{I_p}$ is the normal-incidence P-wave reflectivity and $\frac{\Delta I_S}{I_S}$ is the normal-incidence S-wave reflectivity.

By applying the Fatti equation, simultaneous inversion can be performed on multiple gathers dataset, and then three data bodies, P-wave impedance, S-wave impedance and density, can be simultaneously obtained.

Fig. 1 shows the flow of simultaneous inversion in this paper. The angular gathers are calculated by CRP gathers data of the total reflection points. The initial low frequency model is established by using drilling data, horizon, and fault interpretation results. Time-depth calibration and wavelet extraction are obtained by using well data and sub-angle overlay data volumes. At last, prestack simultaneous inversion can be done by using sub-angle data stack, initial low-frequency model and wavelet. The direct results of simultaneous prestack inversion are P-wave impedance, S-wave impedance, and density. Using these three elastic parameters, we can obtain the S-wave velocity ratio, Lame coefficient, bulk modulus, shear modulus, and Poisson's ratio, etc. The lithology, physical properties and hydrocarbon-bearing prediction of reservoir are completed by using elastic parameters and petrophysical templates.

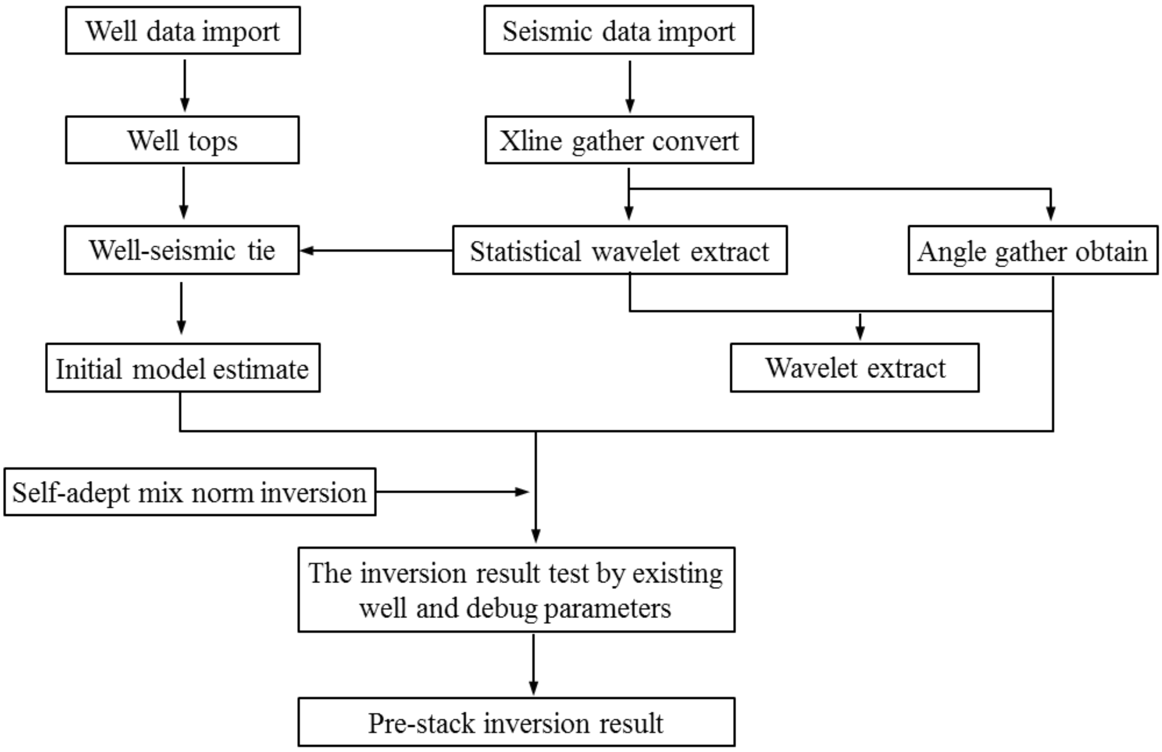


Fig. 1. Prestack simultaneous inversion flow chart.

Adaptive mixed-norm inversion method

In order to predict reservoir effectively, prestack simultaneous inversion is required. Most existing prestack inversion methods assume that the seismic data noise obeys Gaussian distribution, while the actual underground medium noise is complex. Therefore, the deterministic assumptions is not enough to fully characterize the underground situation. In this paper, an adaptive hybrid norm inversion method is proposed to improve the suppression effect of the inversion algorithm on the prestack seismic data noise and to improve the effectiveness of the inversion results.

The random signal can be divided into Gaussian signal and non-Gaussian signal according to whether the probability density function of the signal obeys the Gaussian distribution or not. Gaussian signal refers to the random signal whose probability density function obeys Gaussian distribution. The most important feature of Gaussian signal is the symmetry of the probability density function. The non-Gaussian signal is the stochastic signal whose statistical characteristic deviates from Gaussian distribution. Existing inversion methods, including some mature commercial inversion software, usually assume that noise obeys a Gaussian distribution. However, due to the complexity of seismic data acquisition, it is difficult for the noise to satisfy the Gaussian distribution assumption. So the traditional prestack inversion method based on the Gaussian model is very difficult to achieve powerful results.

Generally, there are mainly Gaussian distribution, super-Gaussian distribution and sub-Gaussian distribution noise in the seismic data. We can usually use kurtosis to distinguish Gaussian, sub-Gaussian, and super-Gaussian types of noise. Kurtosis is a dimensionless parameter, as shown in eq. (2), which is often used to describe the abrupt degree of all value distribution in the whole.

$$\chi(n)=\frac{1}{\mathrm{N}}\sum_{i=1}^{N}\left(\frac{n_i-\bar{n}}{\sigma_i}\right)^4 \quad , \tag{2}$$

where $\bar{n}$ is the mean, σ_i is the standard deviation, and N is the sample length.

According to the magnitude of the signal kurtosis, the signal can be divided into super-Gaussian signal, Gaussian signal and sub-Gaussian signal. Since the second order and above order statistics of the random variables satisfying the Gaussian distribution are equal to zero, the Kurtosis should be equal to zero for the Gaussian distribution. When the Kurtosis is quite different from zero, we can judge that the random variable deviates from the Gaussian distribution. Correspondingly, the signal with a negative Kurtosis is called the sub-Gaussian signal, and the signal with a positive Kurtosis is called a super-Gaussian signal. As described by a more intuitive concept, kurtosis measures the degree of a "peak" of a distribution relative to the Gaussian distribution. In the same variance case, compared to the Gaussian signal, the sub-Gaussian signal has a shorter trailing, and is even more flat in the whole distribution. In other words, the sub Gaussian distribution presents a typical "flat" probability density function: near zero, near a constant, and very small at large values. For example, the uniform distribution is a typical sub-Gaussian distribution.

The traditional L_2 norm has good performance in Gaussian and super-Gaussian environment. At the same time, the inversion algorithm based on L_4 norm has better performance in sub-Gaussian environment. However, there may be many kinds of underground noise. It is very unreasonable to use one distribution feature to suppress the whole three dimensional noise. We should use the weight function corresponding to noise to establish corresponding objective function. For this reason, we propose an mix-norm inversion method, which combines the ability of L_2 norm to process Gaussian and super-Gaussian noise and L_4 norm to deal with the sub-Gaussian noise. Adjusting the weight between L_2 norm and L_4 norm increases the ability of the algorithm to adapt to sub-Gaussian, Gaussian or super-Gaussian noise. Adaptive mix-norm inversion objective function can be defined as the form of eq. (3).

$$\mathrm{J}_1(\mathbf{m}) = [1-\Upsilon(n_b)]\|\mathbf{d}-\mathbf{Gm}\|_2^2 + \Upsilon(n_b)\|\mathbf{d}-\mathbf{Gm}\|_4^4 \quad . \tag{3}$$

The vector **d** is an M × 1 dimensional vector, representing the prestack seismic gathers; G is an M × N dimensional matrix which represents the forward modeling matrix; m is an N × 1 dimensional vector, which is the stratum model parameter we want to obtain, P-wave impedance, S-wave impedance and density. The weight parameter $\Upsilon(n_b)$ controls the weights of the L_2 norm and the L_4 norm, and n_b denotes the background noise. From eq. (3), we can see that: when $\Upsilon(n_b)=0$, the algorithm degenerates into L_2 norm; when $\Upsilon(n_b)=1$, the algorithm degenerates into L_4 norm; and the adaptive criterion should satisfy the following conditions:

a) The adaptive weight parameter should be a function of the inversion error so that the weight is adaptively adjusted;

b) When the noise is Gaussian or super-Gaussian noise, the weight parameter $\Upsilon(n_b)\approx 0$, and the L_2 norm is used. Conversely, when the noise is a sub-Gaussian noise, the weight parameter $\Upsilon(n_b)\approx 1$ and the L_4 norm is used.

Eq. (4) describes the relationship between weight parameter $\Upsilon(n_b)$ and Kurtosis $\chi(n_b)$.

$$\Upsilon(n_b) = f(\chi(n_b)) = \frac{\exp[-c\chi(n_b)]}{A + \exp[-c\chi(n_b)]} \quad , \tag{4}$$

where c and A are positive parameters, usually given by experience. Fig. 2 shows the relationship between $\Upsilon(n_b)$ and $\chi(n_b)$for different values of c and A. As A increases, the weight proportion of the L_2 norm to the L_4 norm increases; as c increases, $\Upsilon(n_b)$ approaches the step function.

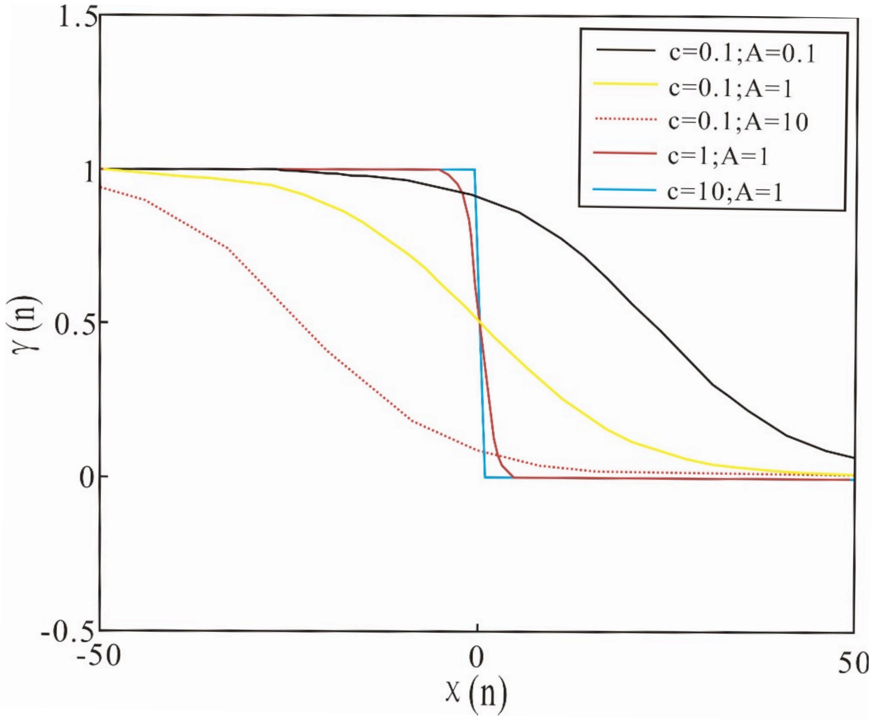


Fig. 2. Relationship between weight parameters and kurtosis under different c and A.

In the above objective function, the regularization parameter is a function of the noise Kurtosis, and the Kurtosis can be calculated by eq. (2).

When the noise is known, we can use eq. (4) to calculate the weight parameter $\Upsilon(n_b)$, but in real seismic prestack inversion, it is hard to get the true noise data. So in this paper, we propose to use iterative residuals n_k instead of true noise data errors n_b to update $\Upsilon(n_b)$. Iterative algorithm equation can be expressed as:

$$\mathbf{m}_k = \mathbf{m}_{k-1} + \alpha_{k-1}\mathbf{P}_{k-1} \quad , \tag{5}$$

where $\mathbf{m}_k$ denotes the k-th iteration result, $\mathbf{P}_{k-1}$ denotes the k-th iteration search direction, and α_{k-1} denotes the search step length. In the actual AVO inversion, the iterative residuals are time-varying, caused by model errors, inversion errors, background noise and some other uncertainties, and show obviously non-Gaussian distributions. Mathematically, it can be expressed as:

$$\mathbf{n}_k = \mathbf{d} - \mathbf{G}\mathbf{m}_k = \Delta\mathbf{G}\mathbf{m}_k + \mathbf{G}\Delta\mathbf{m} + \Delta\mathbf{G}\Delta\mathbf{m} + \mathbf{n}_b \tag{6}$$

where $\Delta\mathbf{G}$ represents the model error between the true forward model and the partial forward model we used, and $\Delta\mathbf{m}$ represents the inversion error between the current iterative model $\mathbf{m}_k$ and the real model parameter $\mathbf{m}$.

Then, the inversion objective function can be expressed as:

$$\mathrm{J}_1(\mathbf{m}) = \left[1 - \Upsilon(n_k)\right]\left\|\mathbf{d} - \mathbf{G}\mathbf{m}\right\|_2^2 + \Upsilon(n_k)\left\|\mathbf{d} - \mathbf{G}\mathbf{m}\right\|_4^4 \quad . \tag{7}$$

Synthetic data test

We use synthetic seismic records to verify the effectiveness of the inversion algorithm. In order to verify the anti-noise performance of the algorithm, we add Gaussian noise with a SNR of 2dB and Laplace noise with non-Gaussian noise of 2dB respectively to the seismic data (Fig. 3). The noisy record is shown in Fig. 4.

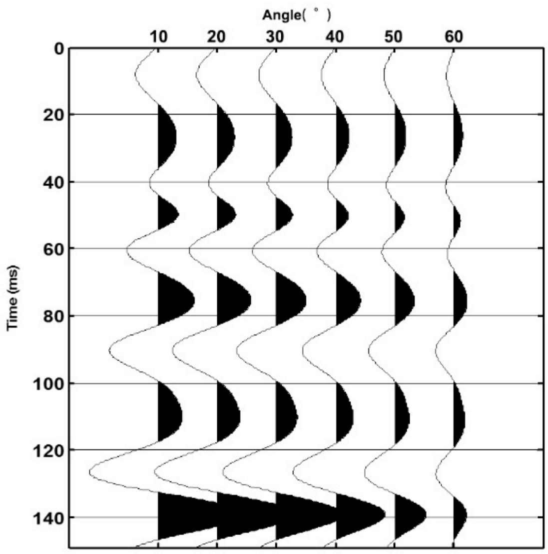
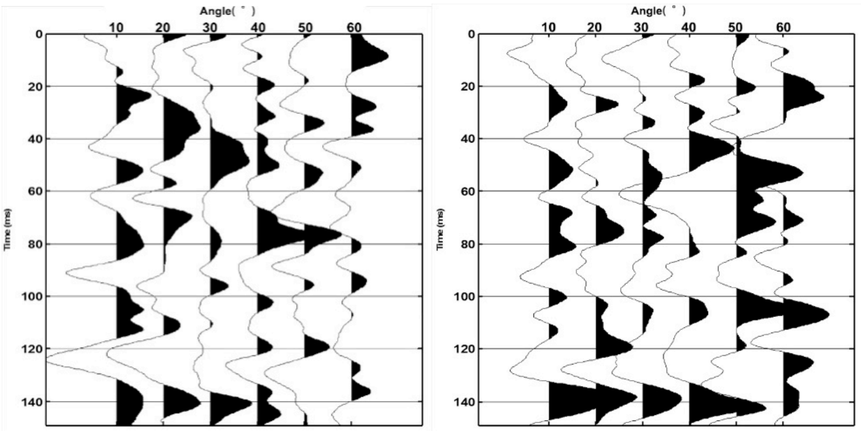


Fig. 3. Noiseless synthetic seismic angle gather.

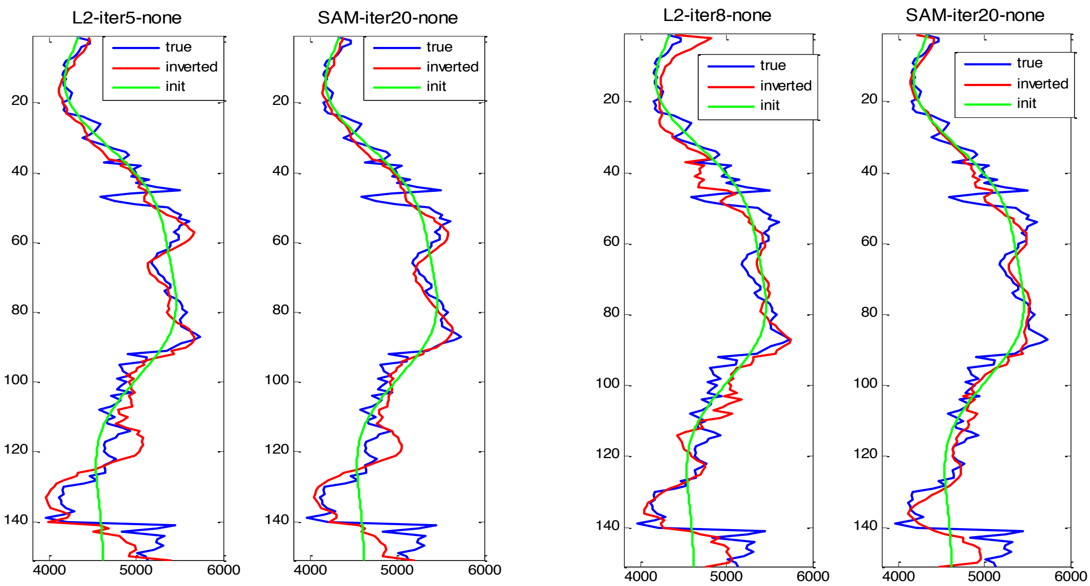
The conventional Gaussian distribution inversion algorithm and adaptive simultaneous inversion methods were compared, as shown in Fig.5. It can be found that the conventional inversion method has good suppression effect on Gaussian noise, but for non-Gaussian noise is not ideal. While the adaptive inversion method has better suppression effect both on Gaussian noise and non-Gaussian noise through the Kurtosis updating iteration. At the same time, we also compare the iterative convergence of the conventional inversion method with the adaptive mixed-norm method. As shown in Fig. 6, the error of the adaptive mix-norm inversion method tends to be stable with the increase in the number of iterations. While the residuals of the conventional Gaussian method will increase with the increase in the number of iterations. Thus, the convergence of the proposed method is obviously stronger than the conventional inversion algorithm.

In summary, the adaptive mix-norm inversion method is obviously better than the conventional method, this paper intends to apply this method to the prestack simultaneous inversion of shale gas reservoirs.



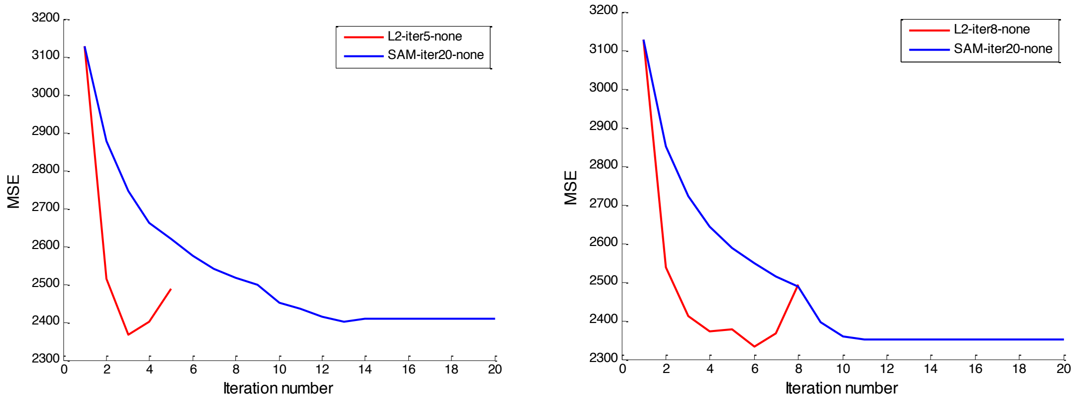
(a) (b)

Fig. 4. Synthetic angle gather of 2dB Gaussian noise (a) and synthetic angle gather of 2dB Laplace noise (b).



(a) (b)

Fig. 5. Comparison of inversion results. (a) Mix-norm inversion results in Gaussian noise environment, and (b) Mix-norm inversion results in Laplace noise environment.



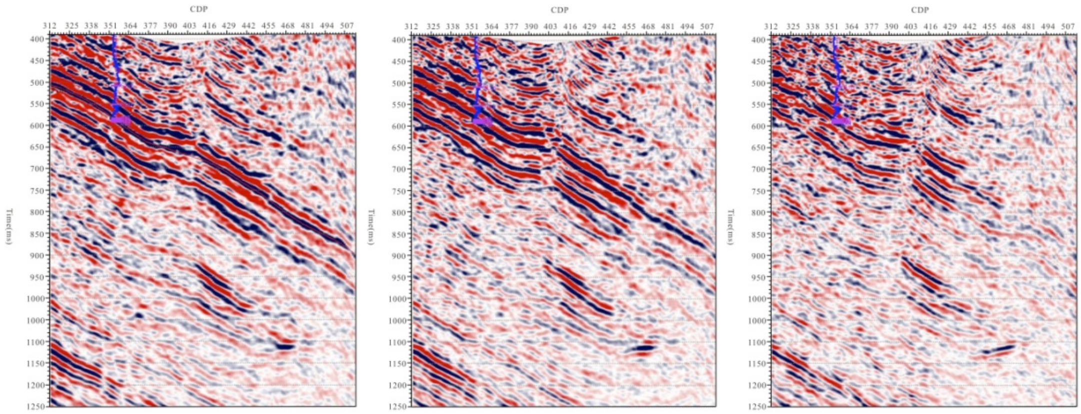
(a) (b)

Fig. 6. Comparison of convergence performance of inversion method. (a) Gaussian noise environment, and (b) Laplace noise environment.

Analysis of partial angle stack seismic data

The prestack inversion technique is different from the post-stack inversion, and the seismic data required for prestack inversion are partial angle stack data. The partial angle superposition data is based on the common reflected point gather data (CRP gather), and is obtained through the stack of different angles. As a result, the quality of the CRP gathers determines the quality of the partial angle stack data. Based on seismic data processing technology, such as prestack denoising, amplitude processing, surface consistency and multiple suppression, we get prestack CRP gather data with relative amplitude preservation, high SNR and resolution. The NMO correction record obtained from conventional data processing is a function of offset. In order to observe and analyze the variation of seismic reflection amplitude with incident angle, it is often necessary to transform the record of offset gathers into the record of incident angle gathers.

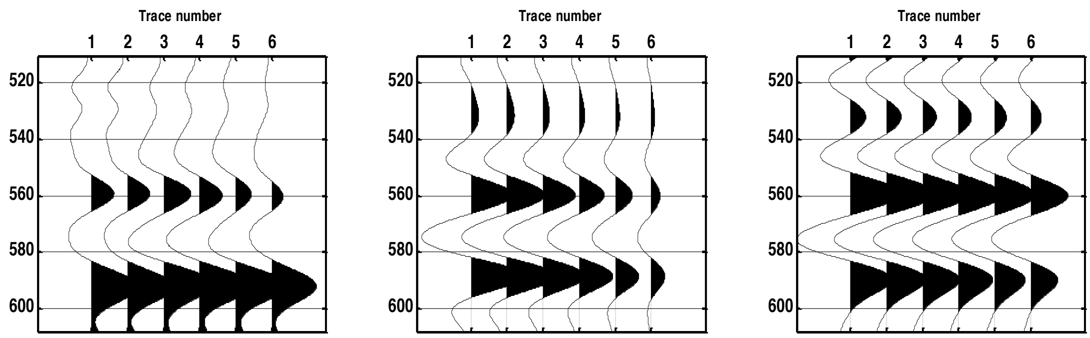
An angle gather refers to the record of the reflected energy from all the different moments from a certain angle of reflection. The angle gather of a certain reflected angle can be obtained by combining the corresponding part of the offset record with the desired reflection angle. Repeat above process for different reflection angles, and different angle gathers are obtained. Based on the estimation of the maximum incidence angle of 3D seismic data and the prediction of the maximum incidence angle of the fluid, combined with the consideration of SNR of the angle stack data, the angle stack scheme of the work area is determined as follows: 5°, -15°, 16°, -25°, 26°, -35°. Fig. 7 shows the three angle stack gathers. It can be seen that the overall SNR of the data is high.



(a) (b) (c)

Fig. 7. Near, middle and far angle stack data profiles.

In order to test the inversion parameters, we conducted a comparative study using forward angle gathers and real gathers. We use the seismic wavelet of well A and the reflection coefficient of well A to synthesize seismic records. As shown in Fig. 8 (b), we can see that the difference between the single wavelet synthesis record and the real wavelet is obvious. The amplitude of the real angle gather increases with the increase of angle, but the amplitude of the synthetic record decreases with the increase of angle. Therefore, the use of a single wavelet may be a problem. In order to further verify our conclusion, we use single wavelet and real gathers as inputs for inversion. After the reflection coefficient is calculated by using the inversion result of impedance inversion, the angle gathers of Well A are synthesized by the single-wave convolution. As shown in Fig. 8 (c), it can be found that there is a significant error in the inversion results obtained by using single wavelet, which is mainly caused by the wavelet itself.



(a) (b) (c)

Fig. 8. (a) True angle gathers over well A, (b) Synthetic seismic records by single wavelet and well A, and (c) Synthetic seismic records by single wavelet and inversion reflection coefficient.

In order to solve this problem, we extract wavelet from different angles separately and then use different wavelet for each angle to calculate. Fig. 9 shows the wavelet extracted from each of the three angle gathers over well A. It can be found that there are obvious energy differences at different angles. The difference of the extracted wavelets is relatively large, which is also the reason for the larger error of single wavelet inversion. We use three wavelet to synthesize seismic records. And three wavelets are used to invert the impedance over the well. The angle gathers are re-synthesized with inversion result and three wavelets, and the records obtained are shown in Fig. 10. It can be found that using the wavelet extracted from each angle can obviously improve the accuracy of the inversion results.

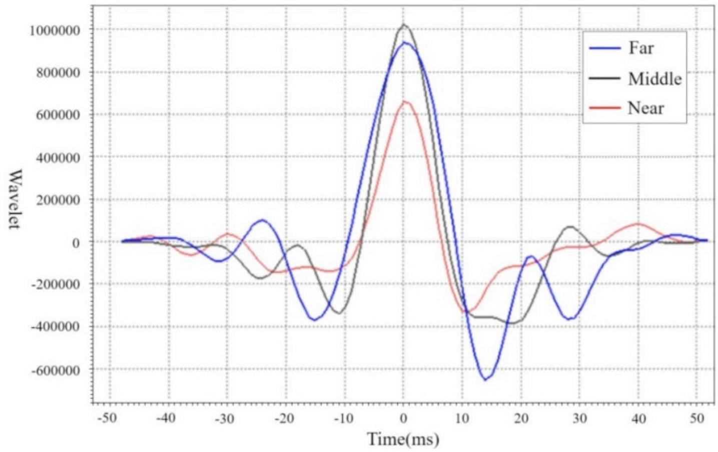


Fig. 9. Extraction of wavelet results from the angle stack data of well A.

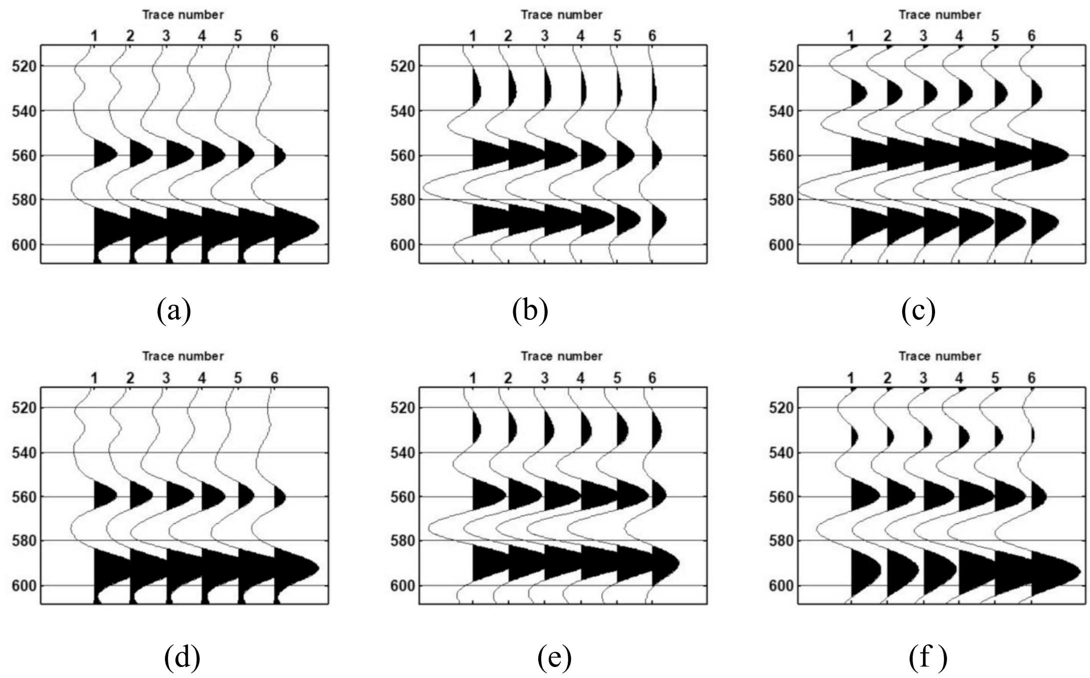
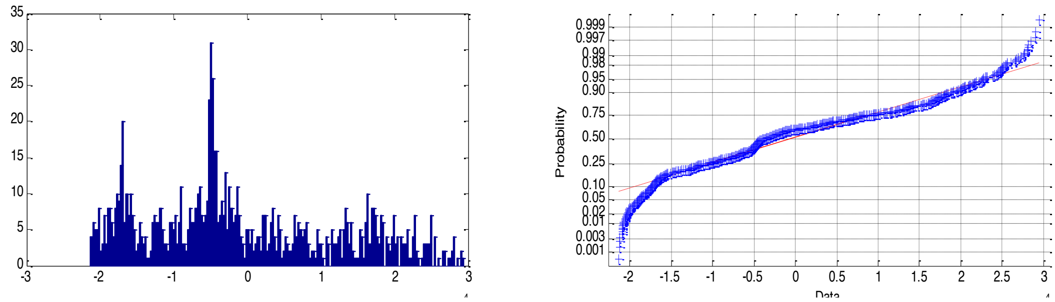


Fig. 10 (a) True angle gathers over well A, (b) Synthetic seismic records by single wavelet and well A, (c) Synthetic seismic records by single wavelet and inversion reflection coefficient, (d) True angle gathers over well A, (e) Synthetic seismic records by multi-wavelets and well A, and (f) Synthetic seismic records by multi-wavelets and inversion reflection coefficient.

Noise analysis

The noise of seismic data is varied. What kind of noise attenuation method should be adopted must first clarify the type and statistical distribution characteristics of noise. We analyzed the noise distribution results of three known logging data in this area. First, synthetic seismic records are calculated by using multiple wavelets in three known wells. Then, the residuals of synthetic seismic records and real records are studied, and the noise distribution characteristics of actual seismic data are judged by residual analysis. As shown in Fig. 11, the error statistics of three wells can be analyzed. It can be found that the errors of well A and well C agree with the Laplace distribution, while the well B error accords with the Gaussian distribution. Therefore, the data noise types in the work area are various, and the traditional least square distribution cannot adapt to all types of noise. Therefore, we intend to use adaptive mix-norm inversion method for calculation.



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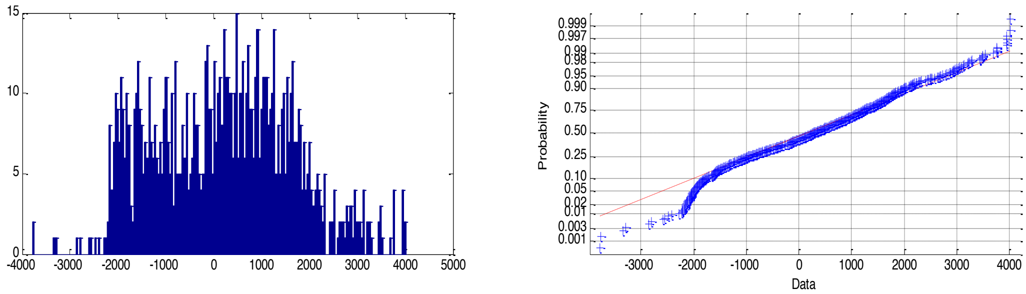

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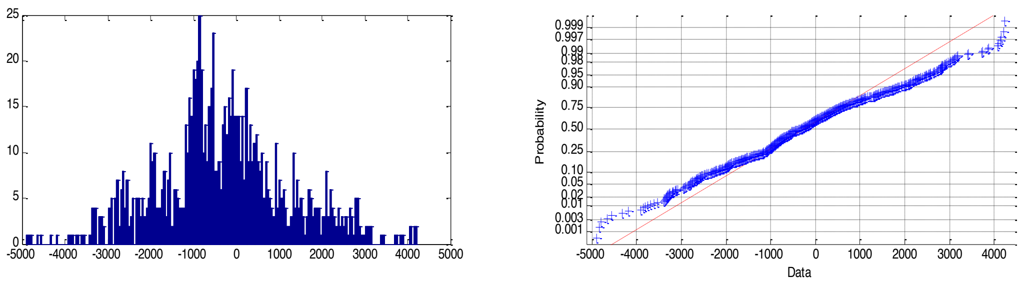


(c)

Fig.11. (a) Well A error distribution, (b) Well B error distribution, and (c) Well C error distribution.

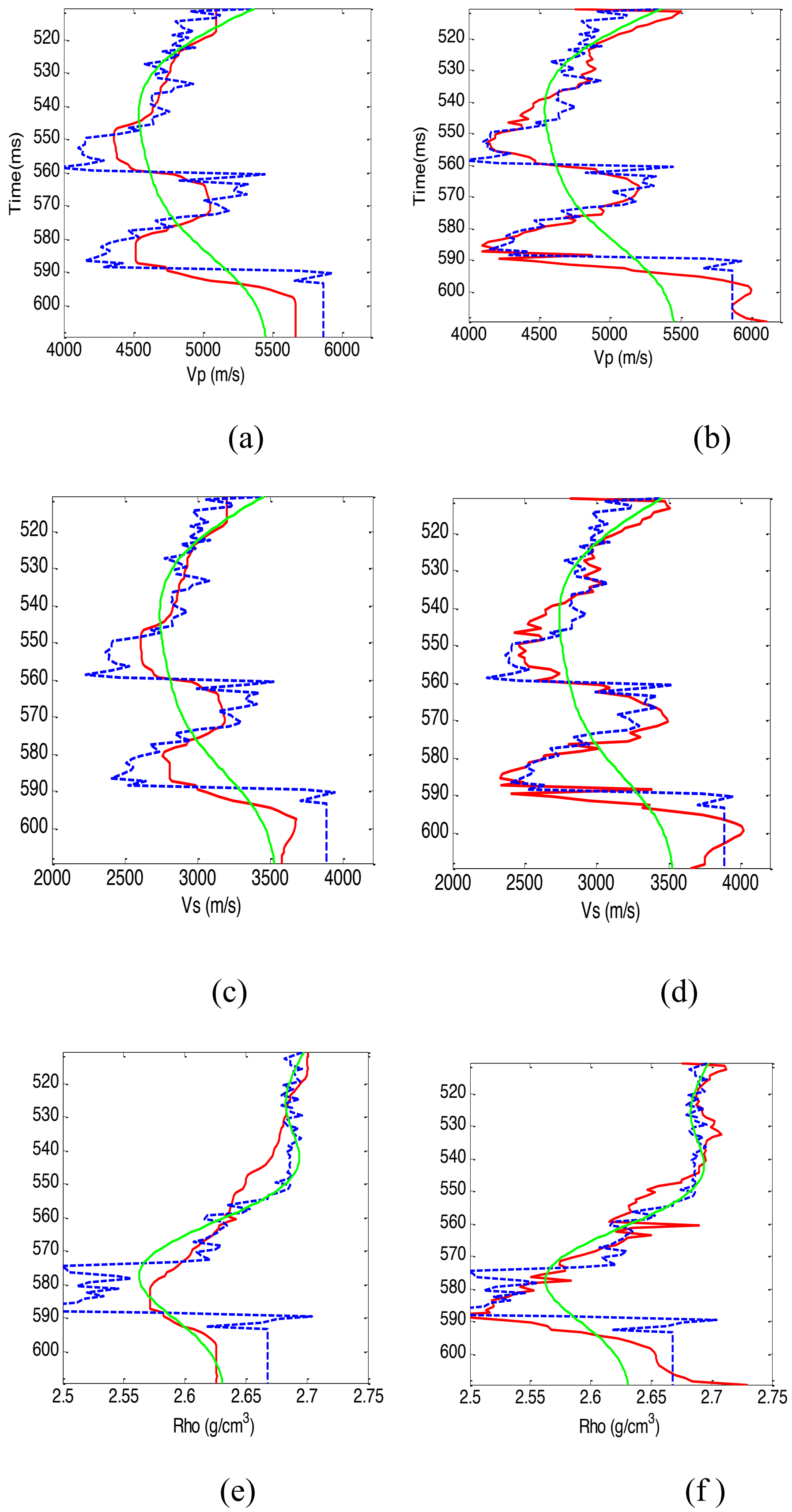
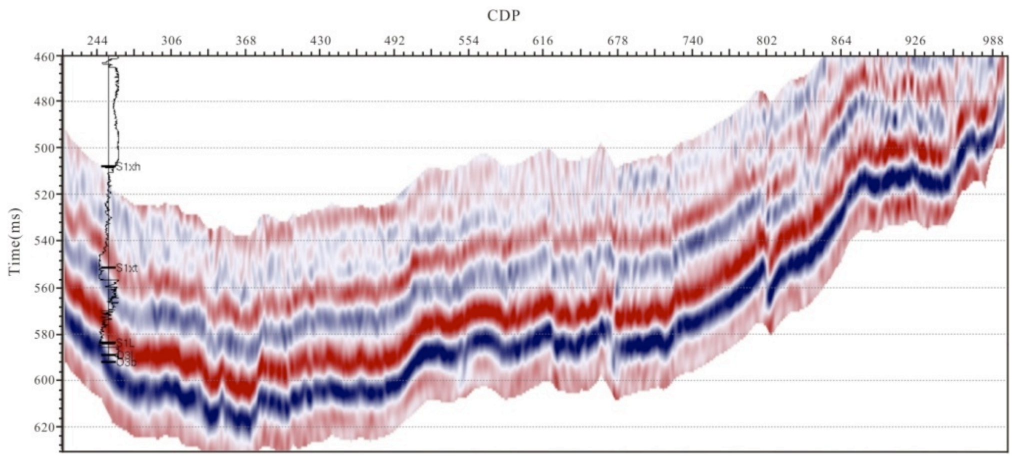


Fig. 12. Comparison of inversion results. Conventional and adaptive mix-norm inversion results of P-wave velocity (a, b), S-wave velocity (c, d), and density (e, f).

In order to illustrate the problem, we compared the results of conventional method and adaptive mixed-norm method for inversion of angle gathers over the well. Fig. 12 is the comparison of the inversion results of single well prestack three parameters in three wells of A, B and C by using multi wavelet. It is found that the inversion result of adaptive mix-norm method is better than that of conventional method.

Inversion results

According to the above analysis, we divide the prestack gather into three angle gathers, and extract the wavelet on each angle gather for inversion. Then we use the adaptive mix-norm method to calculate the three parameters. Finally, we obtain the P-wave velocity, S-wave velocity and density profiles which are shown in Fig. 13. we can find that the inversion result can well show the obvious interface between carbonate and shale. The lithology is clearly distinguished, and the inversion result is in good agreement with the geological conditions.



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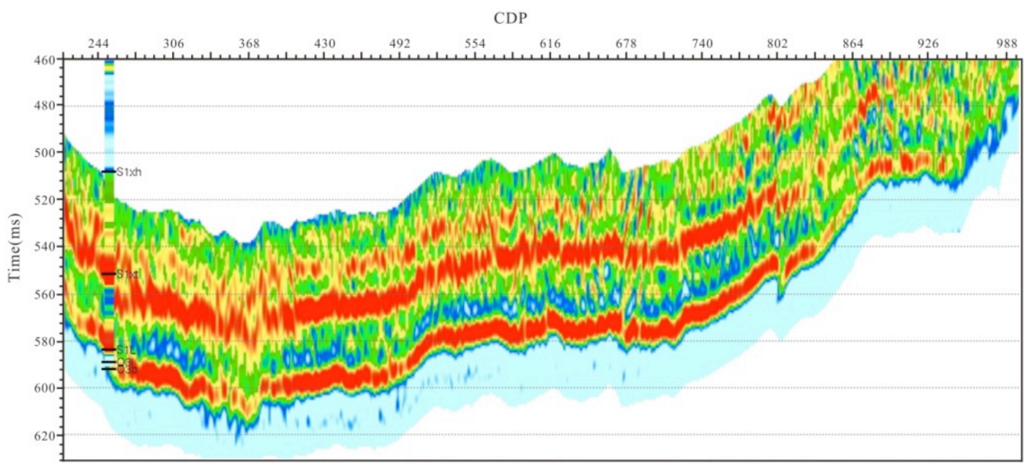

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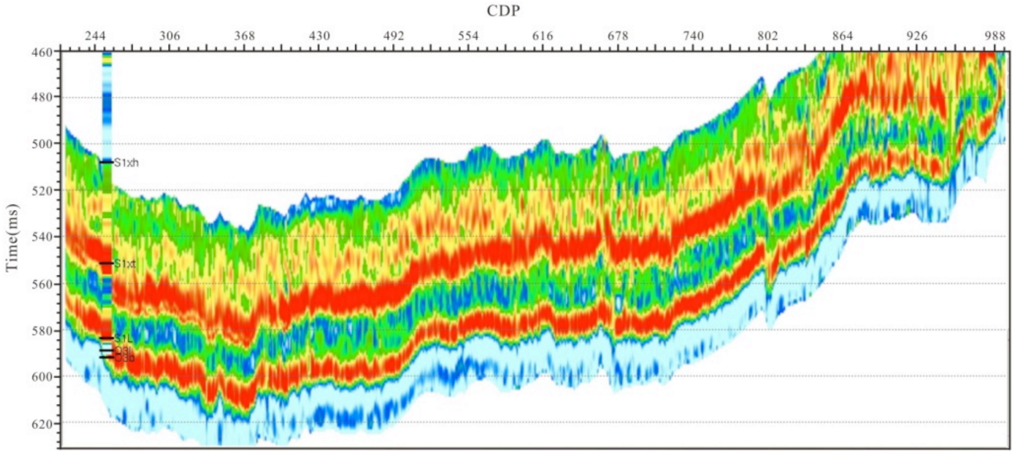
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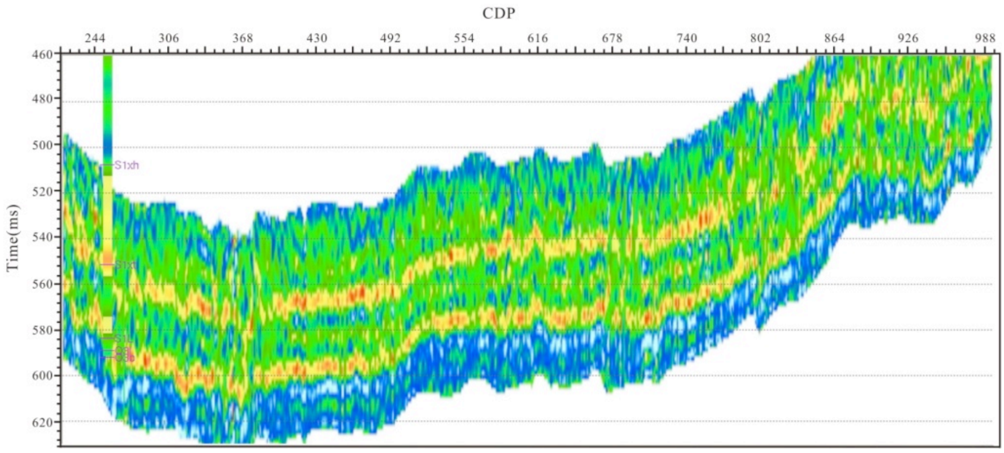
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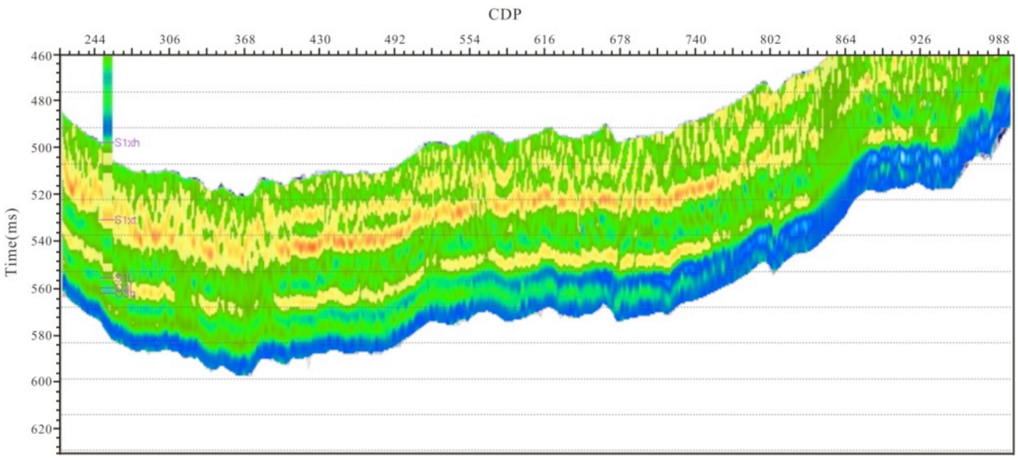
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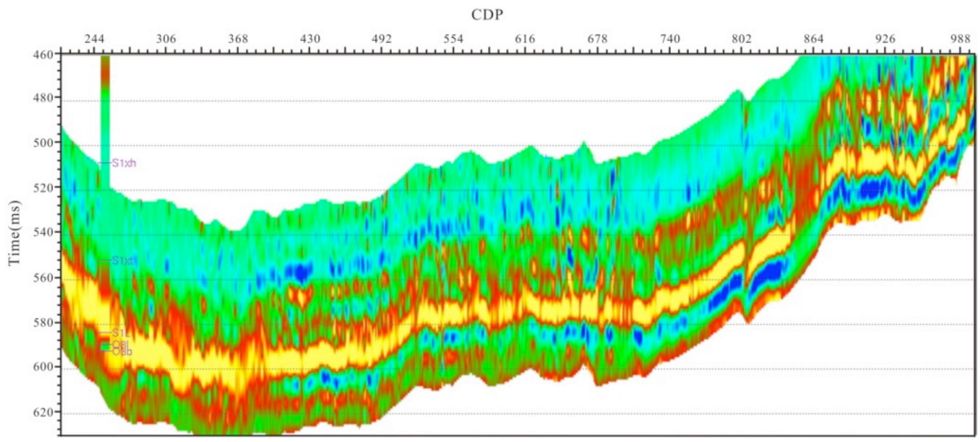
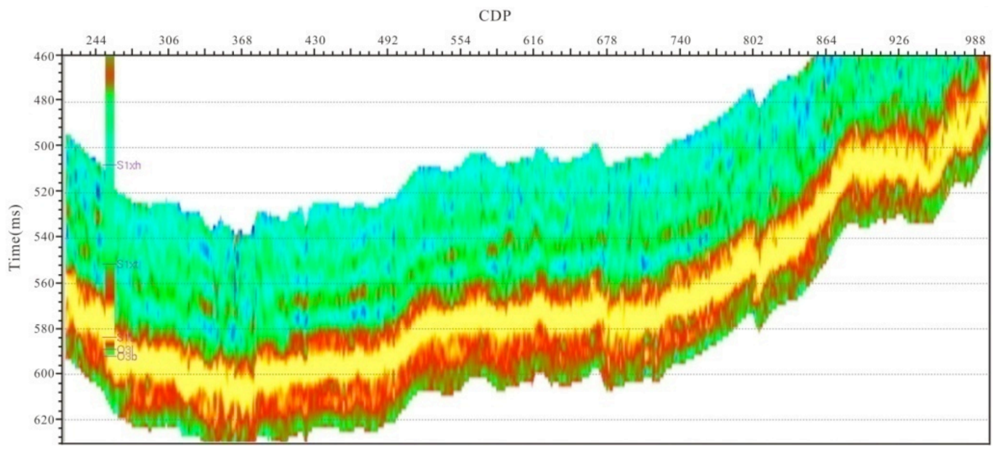
S1xh
S1xt

(e)



(f)



(g)

Fig. 13. Prestack three parameter inversion profiles. (a) seismic data profile, (b) Gaussian inversion P-wave velocity, (c) mix-norm inversion P-wave velocity, (d) Gaussian inversion S-wave velocity, (e) mix-norm inversion S-wave velocity, (f) Gaussian inversion density, and (g) mix-norm inversion density.

CONCLUSIONS

By comparing the Gaussian inversion and non-Gaussian inversion, the non-Gaussian inversion is better than that of Gaussian inversion, the signal-to-noise ratio is higher, the vertical resolution and lateral continuity is better. It is also proved that the noise distribution of prestack data does not completely obey the Gaussian distribution. As prestack data is usually low in signal noise, this method is more meaningful for noise attenuation. Therefore, we use L_2 and L_4 mixed-norm to suppress the noise, gain the weight by Gaussian noise and non-Gaussian noise adaptively, and through the well test and actual data inversion, the denoising effect and feasibility of this method are proved.

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