Research on Image Processing of Signal-to-Noise Ratio and Resolution Based on Seismic Profile

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Abstract. In view of the characteristics of low frequency of seismic data coverage, strong surface interference, low signal-to-noise ratio and low resolution, this paper studies a set of pre-stack combined denoising technology, adaptive predictive deconvolution technology, anisotropic motion Correction and high-precision speed analysis, Kirchhoff restack time migration imaging and other key technologies are the core processing methods. The layer-by-layer similarity learning method is used to reconstruct high-resolution images, especially when the image is enlarged, it can still be clearer. Restore the detailed features of the texture of the seismic profile image. The actual profile test shows that the quality of image reconstruction has been improved, and good results have been obtained in terms of visual effects and peak signal-to-noise ratio.

1. Introduction
At present, the signal-to-noise ratio and clarity of three-dimensional seismic data in many sections and key geological structures cannot meet the requirements of correct interpretation. How to suppress the noise of low SNR seismic data and improve the signal-to-noise ratio of seismic records to facilitate interpretation is a very important issue. Shallow seismic exploration is a major exploration technique used in engineering geophysical prospecting. It is widely used in geological survey, structural survey, active fault survey, coal seam goaf survey and geological disaster survey. This method mainly uses the formation information carried by shallow seismic reflection waves to determine the shape of underground structures, and uses high-quality seismic interpretation profiles to intuitively reflect the underground structures. The author first uses optimized TV denoising technology to remove the seismic data noise and improve the signal-to-noise ratio of seismic data, and then uses the layer-by-layer similarity learning method to further improve the seismic profile image resolution. The high-quality profile obtained in this way can accurately reproduce the underground geology, to make a more reasonable oil and gas evaluation of the survey area [1].

2. Image edge detection method
We used Roberts, Prewitt, Sobel, LOG, and Canny edge detection methods to perform edge detection on a measured seismic profile. After comparison (Figure 1), we found that the detection effect of using Canny edge detection method is better than other methods. Canny operator can More subtly edge detection, the image edge information is retained to the greatest extent. Of course, for seismic data, the
Canny operator will also inevitably retain more noise edge detection results. Later we will deal with speckle edges (more corresponding to noise) that have been eliminated so that some noise edges of the image can be eliminated. Below, we will introduce the Canny operator in more detail:

The Canny operator is a first-order operator. The essence of its method is to use a quasi-Gaussian function as the smoothing operation \( f_s = f(x,y) + G(x,y) \), and then use the directional first-order differential operator to locate the maximum derivative. After the smoothing, the gradient of \( f_s(x,y) \) can be a 2 × 2 first-order finite difference approximation:

\[
P(i,j) \approx \left[ f_s(i,j+1) - f_s(i,j) + f_s(i+1,j+1) - f_s(i+1,j) \right] / 2
\]

\[
Q(i,j) \approx \left[ f_s(i,j) - f_s(i+1,j) + f_s(i,j+1) - f_s(i+1,j+1) \right] / 2
\]

Find the average of the finite difference within this 2 × 2 square to facilitate the calculation of the partial derivative gradient of x and y at the same point in the image. The amplitude and direction angle can be calculated by the coordinate conversion of rectangular coordinates to polar coordinates:

\[
M(i,j) = \sqrt{P(i,j)^2 + Q(i,j)^2}
\]

\[
\theta(i,j) = \arctan \left( \frac{Q(i,j)}{P(i,j)} \right)
\]

M [i, j] reflects the edge strength of the image; \( \theta [i, j] \) reflects the direction of the edge. The direction angle \( \theta [i, j] \) that makes \( M [i, j] \) obtain the local maximum reflects the edge. The direction of the Canny operator can also be approximated by the gradient of the Gaussian function, which is theoretically very close to the best edge operator formed by the linear combination of four exponential functions [2].

3. Key technology in shallow seismic data processing

3.1. Pre-stack combined denoising technology

Shallow seismic data has its own unique characteristics. The reflection layer is shallow, and it is greatly interfered by the environment and human activities. The effective wave and linear noise are similar in apparent velocity and frequency. Interference and high-frequency interference and other noise masking, the number of shallow recognition noise channels is small, so higher requirements are placed on the denoising technology. By formulating a reasonable combined denoising technology, the effect of improving the signal-to-noise ratio is achieved, so that the effective signal is better retained. The comparison of the single shot records before and after the pre-stack combination denoising is shown in Figure 1.
Figure 1. Comparison of geological space before and after denoising

It can be seen from Figure 1 that in the single shot recording after denoising, the surface wave and linear regular noise suppression effect is better, and the effective signal is better protected, and the resolution is further improved [3].

3.2. Deconvolution technology

Although the signal-to-noise ratio of shallow seismic data has been greatly improved after pre-stack denoising, due to the shallow reflection layer, the surface structure changes greatly, the effective wave is confused with the multiple wave, and the existence of multiple wave seriously affects the seismic imaging the authenticity and reliability of the data reduce the resolution of the data. Therefore, eliminating multiple waves is another key point in the processing of shallow seismic data. Although the method of predicting deconvolution to attenuate multiples can effectively attenuate multiples, it still has the problem of many multiples remaining. Therefore, by designing an adaptive filter, the iterative formula of the least mean square algorithm is used to update the key parameters of the adaptive prediction deconvolution. Combining parameters such as prediction factors, prediction steps, and factor lengths with the distribution period and distribution range of the multiple wave, the deconvolution parameters can be set in a targeted manner to suppress the multiple wave and improve the resolution.

Figure 2. Comparison of adaptive predictive deconvolution before and after application
The comparison between before and after the application of adaptive predictive deconvolution is shown in Figure 2. It can be seen from Figure 2 that multiple waves and residual low-frequency surface waves cover up effective waves, especially in the near-channel ultra-shallow period, where effective waves are mixed on the same-phase axis, and there is a serious resolution problem. After adopting the adaptive predictive deconvolution technology, the multiple wave is effectively suppressed, the seismic wavelet compression effect is good, the effective wave in-phase axis is continuous and clear, and the resolution is greatly improved, which lays an important role for the later imaging effect and interpretation accuracy.

3.3. Super-resolution image reconstruction

Super-resolution is to increase the resolution of the original image through hardware or software. The process of obtaining a high-resolution image through a series of low-resolution images is super-resolution reconstruction. High resolution means that the pixel density in the image is higher and can provide more details, which are indispensable in many practical applications. The problem of super-resolution reconstruction can be divided into two categories according to the number of input images: multi-image and single-image. 1. Multi-image super-resolution refers to the use of a series of images (or part of a video) for reconstruction, they all contain highly relevant information (i.e. relative scene motion); 2. Single-image super-resolution reconstruction the technology improves the image resolution by enlarging the image while enhancing the details. It is suitable for various situations where the image sequence of the same scene cannot be obtained [4] (such as the restoration of ancient cultural relics, instant imaging of high-speed moving objects, unable to reproduce or continuous shooting Medical image processing, etc.). In order to combine the useful information in the reconstructed image in a certain way and integrate a high-quality image, it is necessary to select the appropriate training set and neighbourhood set for learning. According to the local correlation characteristics of the image, it is assumed that both the training set and the neighbourhood set come from a distribution model. The mathematical model is shown in Figure 3.

Local geometry refers to the contribution of the neighbouring pixels to the central pixel in a set. The correspondence between the contribution of the neighbourhood window and the training window is called local geometric similarity. The coefficient $\beta$ represents the local geometric structure of the neighbourhood window and the training window [5]. This local geometry of the training window can be transferred to the neighbourhood window by learning the local geometry of the training window, that is, all training windows in the training set satisfy a unified mathematical model, all $m$ training windows $B(\xi, n)$ satisfy the formula (5), thus obtaining the estimated value of the optimal solution $\hat{\beta}$:

$$\hat{\beta} = \arg\min_{\beta} \| x - x' \|$$

$$\begin{bmatrix} \beta_1, \beta_2, ..., \beta_n \end{bmatrix}$$ is a vector of $n$ * 1 columns, and $\sum_{i=1}^{n} \beta_i = 1$. 

Figure 3. Mathematical model
4. Example analysis
The result of edge detection is the envelope of the abrupt gray area, and it cannot be directly used as the detection result of the in-phase axis. It is necessary to perform further processing in combination with the gray-scale characteristics of the image of the reflection of the seismic phase stratum to detect the correct in-phase axis. The characteristic that the gray value of the reflection in-phase axis is large, write a program to judge whether the gray value of the original image between adjacent edge lines is greater than a certain threshold (the threshold here can be adjusted according to the actual situation of the profile), if If the conditions are met, the original edge result is zero, and the central axis of the original edge result is taken as the new edge result. After the actual data processing (Figure 4), it is proved that the central axis of the strong gray envelope is extracted as the detection result of the in-phase axis, The correct in-phase axis detection result is obtained [6].

The crack information will be blurred due to noise interference. In order to improve the effect of crack detection, it is necessary to denoise before crack detection. The above shows that only by using edge-preserving denoising data for crack detection, it is possible to obtain better geological results. If smooth filtering data is used for crack detection, the processing result will seriously distort the underground geological structure. Figure 4 is a crack detection diagram made directly without edge-preserving denoising in a certain area. Figure 4 is a crack detection diagram made after making edge-preserving denoising. Although the former can also reflect the distribution of cracks from a macro perspective, it is sporadic and disorderly. The latter appears more regular [7].

Seismic profiles with similar geological structures but different signal-to-noise ratios were subjected to mean filtering and 2D along-layer filtering, respectively. According to equations (2) and (3), the signal-to-noise ratio and the change in signal-to-noise ratio of the seismic profiles before and after processing were calculated. Table 1 lists the processing results of three sets of geological profiles with similar structures but different noise strengths. At the same time, the changes in signal-to-noise ratio and signal energy retention are given. As can be seen from Table 1, two-dimensional along-layer filtering and mean the effect of filtering, no matter how high or low the signal-to-noise ratio of the original image, the signal-to-noise ratio has increased significantly. The lower the original signal-to-noise ratio, the more the increase after processing; The along-layer filtering is about 20% higher than the mean filtering [8].
Table 1. SNR improvement (dB) and signal energy retention

| 2D along-layer filtering of processed image | Mean filtering and its SNR | 2D along-layer filtering SNR | Mean filtering SNR | Signal energy retention (%) | SNR | Signal energy retention (%) |
|-------------------------------------------|---------------------------|-----------------------------|-------------------|-----------------------------|-----|-----------------------------|
| Similar junction high SNR                 | 17.79                     | 3.43                        | 83.5              | 3.33                        | 59.31 |
| Construction 1 low SNR                    | 9.61                      | 8.9                         | 80.24             | 8.22                        | 61.16 |
| Similar junction high SNR                 | 17.81                     | 3.46                        | 84.12             | 3.43                        | 60.45 |
| Construction 2 low SNR                    | 9.63                      | 8.96                        | 81.07             | 8.29                        | 62.2  |
| Similar junction high SNR                 | 17.95                     | 3.59                        | 84.4              | 3.44                        | 60.19 |
| Construct 3 low SNR                       | 9.67                      | 9                           | 81.01             | 8.25                        | 62    |

5. Conclusion
The author uses the image processing method to improve the signal-to-noise ratio of the seismic section through the optimized Canny algorithm to better maintain the image edge, and then uses the layer-by-layer similarity learning method to select the appropriate training window through the neighbourhood window to obtain High resolution value. Realize the self-repair of the unknown area of a single image. The result analysis shows that the processed image not only improves the resolution of the original image, but also retains more and more effective information, which is convenient for the later seismic interpretation work.

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