Introduction

Seismic data fault detection is of great significance for effectively understanding the macroscopic distribution of underground faults. Seismic attributes are often used as methods for seismic fault detection, and there are many types. At present, the most widely used coherent algorithms, structural tensor algorithms, etc. However, affected by lithology, physical properties, and data collection and processing methods, the quality of seismic data varies widely, which can easily lead to large differences in detection results and uneven spatial fault distribution. Figure 1(a)(b) shows the comparison of the seismic profile and the corresponding coherence attribute profile, respectively. It can be seen from the figure that areas with large differences in wave impedance have strong signal energy, high signal-to-noise, and weak interference in fault detection. The areas with small differences in the impedance have complex responses and low signal-to-noise ratios, and the fault response is masked by the response caused by noise. It can be seen on the coherence profile that the coherence attribute changes unevenly when the local signal-to-noise ratio of the seismic data changes. The noise disturbs the fault attributes, which is different from the real space distribution characteristics of the fault. To solve this problem, this paper proposes a quality evaluation algorithm based on seismic images entropy to evaluate the reliability of seismic data. Then the evaluation results are used to suppress the fault attributes where the less reliable part of the seismic data locate and enhance the fault attributes of the higher reliability. This method achieves the goals of adjusting the fault attributes, making the fault attributes balanced, and optimizing the fault attribute response patterns.

Figure 1 this is a comparison of data profile from same area. seismic data in figure1(a), fault attribute(coherence attribute) data in figure1(b). It shows that the noise has greater influence to fault attribute where energy of seismic data is low.

Seismic image entropy evaluation method

Entropy is a concept used in information theory to measure information uncertainty. In 1948, Shannon introduced the concept of entropy into information theory, which represents the uncertainty of the system (source) and is used to measure the amount of information. It is called "information entropy". When entropy is larger, the information contains more uncertainty, and the information is less reliable. The information entropy called image entropy when use in image field, which indicates how much useful information is in the image. Image entropy can be used to indicate the degree of chaos in the image. The larger the entropy, the more chaotic the image, and the less clear the target information; the smaller the entropy, the clearer the image, and the clearer the target information. Therefore, we use image entropy as the basis for evaluating the reliability of seismic data.

The one-dimensional entropy of the image represents the amount of information contained in the aggregated features of the gray distribution in the image. Pi is the proportion of pixels in the image with a gray value of i, then the one-dimensional gray entropy of the image is defined as formula(1):

\[ H = - \sum_{i=0}^{255} p_i \log p_i \]  (1)
The neighbourhood gray value of the image is selected as the spatial feature of the gray distribution, and a feature two-tuple is formed with the pixel gray of the image, denoted as \((i, j)\), where \(i\) represents the gray value of the pixel \((0 \leq i \leq 255)\):

\[
P_{ij} = f(i, j) / N^2
\]  

(2)

The above formula can reflect the comprehensive characteristics of the gray value at a pixel position and the gray distribution of the surrounding pixels. Among them, \(f(i, j)\) is the frequency of the feature tuple \((i, j)\). The discrete two-dimensional entropy of the image is:

\[
H = -\sum_{i} \sum_{j} P_{i,j} \log P_{i,j}
\]  

(3)

We use image two-dimensional entropy algorithm to perform entropy evaluation on seismic data. The specific process is as follows:

**Figure 2** (a)Seismic entropy calculation flowchart, (b) Schematic diagram of amplitude binary ten-channel discrete coding.

For the three-dimensional data volume, the principle of calculating point-by-point method according to depth (time), trace and line is adopted, and each point is processed according to the seismic entropy calculation flowchart. Firstly, a time window is selected with the calculation point as the center point, and all points in the time window are normalized to the interval \([-1, 1]\). Secondly, based on the normalized amplitude value, encoding is performed according to the schematic diagram of the amplitude encoding, figure2 (b), and the amplitude is binary encoded to generate a ten-bit encoding channel, which is divided into 1024 categories \((2^10)\). The advantage of this processing is that the ten-bit binary coding has the advantage of higher classification accuracy than gray distribution which only has 255 level, is not affected by the background amplitude value of the original data, and is easy to locate and store. Thirdly, the probability of sample points in the neighborhood is calculated, and the local entropy of the seismic image of the calculated points is obtained. Finally, the local entropy attribute volume can be obtained by performing a point-by-point scan on all samples of the 3D seismic data volume to calculate the local entropy of the image.

The entropy value represents the reliability of the fault attribute body generated from seismic data. Using the seismic entropy as a weighting coefficient, the high reliability region of the fault attribute is enhanced, and the low reliability region is weakened, which can optimize the fault attribute.
Examples

The method was tested on the actual data. From the results of the seismic data and its entropy estimation, it can be seen that when the amplitude of seismic events are large, the seismic image entropy respectively get a low value, which means seismic data is in a high degree of order, and the signal is far greater than the noise. So the fault attribute is highly reliable, otherwise the reliability is low. This verifies the correctness of our method.

![3D seismic data](image1)
![Seismic image entropy attribute generating from (a)](image2)

*Figure 3* (a) 3D seismic data (b) Seismic image entropy attribute generating from (a)

We extracted seismic data profile and compare the corresponding entropy attribute profile(figure 4 a, b), structural tensor fault attribute profile, and structural tensor fault attribute profiles adjusted by seismic image entropy(figure 5 a, b).

The discontinuity of seismic data caused by real faults did not cause a significant increase in entropy because the proportion of data with fault locations in the 3D time window was low. The noise affected a large proportion of the area, and the entropy increased significantly. Therefore, after adjusting the fault attributes through entropy, the clutter interference to fault attributes caused by seismic noise at weak amplitudes is effectively suppressed, and the response of the fault was highlighted, and good results have been achieved.

![seismic data profile](image3)
![Entropy attribute profiles](image4)

*Figure 4* (a) seismic data profile (b) entropy attribute profiles
Conclusions

Seismic noise will have a greater impact on weak signals, and this effect is reflected on fault attributes, affecting the ability to detect the faults. The 3D seismic image entropy can effectively evaluate the reliability of fault attributes from seismic data in different regions. Seismic image entropy is sensitive to noise and not sensitive to fault. Therefore, after the evaluation of seismic data, it is used to optimize the fault data by suppressing the response of seismic noise in fault attributes, and highlighting information of fault component. Experimental results support this conclusion.

References


