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Artificial Intelligence Minor Fault Identification Technology and Its Application in BD1 Area

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Abstract: Traditional fault interpretation mainly relies on human-machine interaction, which has low efficiency and high human uncertainty. Coherence attribute is sensitive to the discontinuity characteristics of seismic data and can effectively identify high grade faults. The coherence algorithm has undergone three innovations: cross-correlation (C1), similarity (C2), and eigenstructure (C3). In addition to coherence, attributes such as curvature, dip angle, and ant tracking have been proposed, and the likelihood attribute has developed rapidly in recent years, which can accurately reflect larger fault structures and has certain discrimination ability for small faults. However, due to the small moment and short extension length of low grade faults, they do not necessarily exhibit discontinuous characteristics at the fault location (especially for strike-slip faults), and the traditional attributes have not achieved good results in identifying small-scale faults. With the development of artificial intelligence algorithms in the field of target detection, advanced neural networks have proven to surpass traditional attributes in identifying faults from seismic data. This article takes the BD1 area of the Sichuan Basin as an example and combines fault enhancement interpretive processing such as dip scanning, structure-guided filtering, edge-preserving filtering, and frequeency filtering with artificial intelligence algorithms and transfer learning techniques for low grade fault identification research, forming a precise and reasonable artificial intelligence low grade fault identification technology process. The results show that the artificial intelligence algorithm using a large sample library can identify low grade faults that cannot be detected by traditional methods, and the fault detection results of artificial intelligence are superior to traditional attributes in terms of noise resistance, accuracy, and computational efficiency.

Keywords: Low Grade Fault, Discontinuity Attribuet, Fault Enhancement, Artificial Intelligence, Large Sample Library, Transfer Learning

1. Introduction

Seismic fault interpretation is a key task in establishing the Earth's reservoir model, and high-precision, high-efficiency, and high-resolution fault identification results are important guarantees for accurate geological structure interpretation. However, how to accurately and efficiently identify faults from seismic data has become a major challenge, especially the identification of low-grade faults has become one of the key technologies in high-resolution 3D seismic interpretation.

Currently, the conventional methods for fault identification and characterization mainly rely on attribute extraction techniques such as coherence (C1, C2, C3) [1-3], curvature [4-7], ant tracking [8-9], and maximum likelihood volume (likelihood) [10-11]. Additionally, various attributes are further combined, such as multi-information and multi-attribute fusion identification techniques that incorporate frequency, azimuth, and other information [12]. These techniques have become relatively mature, but there are still issues with low accuracy in fault characterization and low efficiency in identification, making it difficult to meet the requirements for fine characterization in exploration and development objectives.

Low-order faults have small fault slip and short extension length, and their positions may not exhibit discontinuous features (especially for strike-slip faults). Traditional methods face significant challenges in identifying low-order faults. In recent years, with the rapid development of science and technology, artificial intelligence [13-14] and machine learning techniques [15-16] have been widely applied in various disciplines. With the advancement of artificial intelligence algorithms in the field of object detection, applying artificial intelligence algorithms for fault identification has achieved good results and made significant progress in improving fault interpretation efficiency, reducing subjective interpretation, and enhancing automated seismic fault interpretation. It has been proven that it surpasses traditional attributes in identifying faults from seismic data.

To address the challenge of identifying low-order faults and strike-slip faults with small fault slip and short extension length, this study combines fault enhancement interpretation techniques such as dip scanning, structure-guided filtering, edge-preserving filtering, and band-pass filtering with artificial intelligence algorithms and transfer learning techniques [17] for low-order fault identification research. This approach forms a refined and rational workflow for artificial intelligence-based low-order fault identification. The results show that using artificial intelligence algorithms with a large sample database can identify low-order faults that traditional methods fail to detect. The artificial intelligence fault detection results surpass traditional attributes in terms of continuity, noise resistance, accuracy, and computational efficiency. Additionally, by introducing transfer learning strategies and training the network with a small amount of manually labeled seismic data samples, the network can learn more actual fault features. The transfer learning identification results effectively reduce cases of missed detection and misidentification, thereby improving the accuracy and reliability of low-order fault identification.

2. Research on Artificial Intelligence Fault Interpretation Technology

2.1. Fault Enhancement Interpretation Processing

During the acquisition and processing stages of seismic data, various factors can lead to low signal-to-noise ratio and poor imaging quality, resulting in fuzzy fault information in the seismic data. This hinders the detection and identification of faults, thus affecting the accuracy of seismic data interpretation. Therefore, it is necessary to use fault enhancement techniques to reduce noise and enhance the signal of faults in seismic data, making the fault depiction clearer. Subsequently, the enhanced faults can be detected and identified to improve the accuracy of seismic data interpretation. The workflow is illustrated in Figure 1.

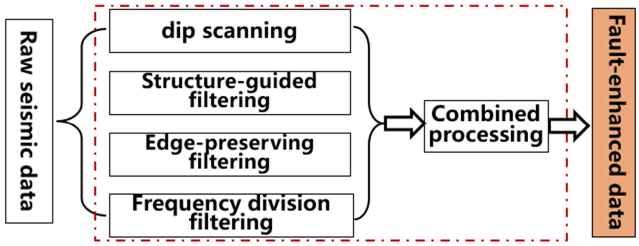


Figure 1. *Fault Enhancement Interpretation Processing Flowchart.*

This study mainly combines methods such as dip scanning, structure-guided filtering, edge-preserving filtering, and Frequency division filtering, and iteratively optimizes them multiple times to enhance the response characteristics of fault seismic data. This improves the ability to identify faults and reduces interpretation ambiguity.

Dip scanning considers the actual dip and azimuth of the geological formation. It tracks and compares along the dip direction of the formation reflection to obtain more accurate geological target information, resulting in an accurate dip and azimuth volume.

Structure-guided filtering applies anisotropic diffusion filtering to seismic data under the control of the dip and azimuth volumes. It reduces noise in seismic profiles, improves the signal-to-noise ratio of seismic data, and makes the faults associated with fault-related synclines or distortions more clear and prominent.

Edge-preserving filtering is a complementary application of maximum likelihood attributes. It is a non-linear filter with constructed constraints for edge preservation. It removes background interference noise while avoiding blurring of discontinuous structural features such as faults and geological body edges, ensuring the preservation of geological structures and sedimentary information.

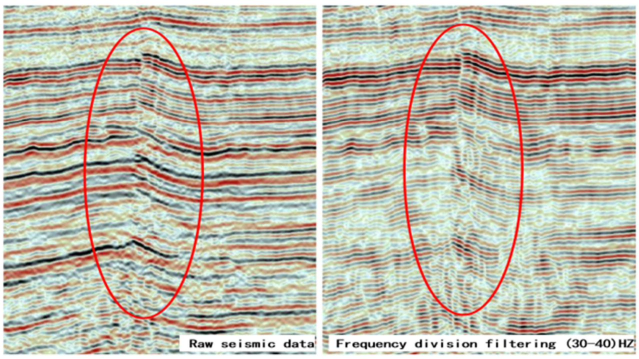


Figure 2. *Comparison profile before and after frequency division filtering.*

Frequency division filtering utilizes spectrum decomposition techniques to decompose the full-frequency seismic data into multiple frequency bands, thereby obtaining geological seismic information contained in different frequency ranges. The use of medium to high-frequency data can significantly improve the detection capability of low-amplitude faults and also has a strong denoising effect. Figure 2 shows a comparison profile before and after band-pass filtering. The left side of Figure 2 represents the original seismic profile, while the right side represents the 30-40Hz frequency division profile. From the Figure, it can be observed that the low-grade faults are more clearly identifiable in the medium to high-frequency data.

Figure 3 shows a before-and-after comparison of seismic data interpretation processing. The left side represents the original seismic data, while the right side represents the seismic data after fault enhancement processing. From the Figure, it can be observed that the seismic data after fault enhancement processing has effectively removed noise and preserved the seismic response characteristics at fault locations. Through fault enhancement techniques, the faults in the seismic data are both noise-reduced and signal-enhanced, resulting in a clearer depiction of low-amplitude faults.

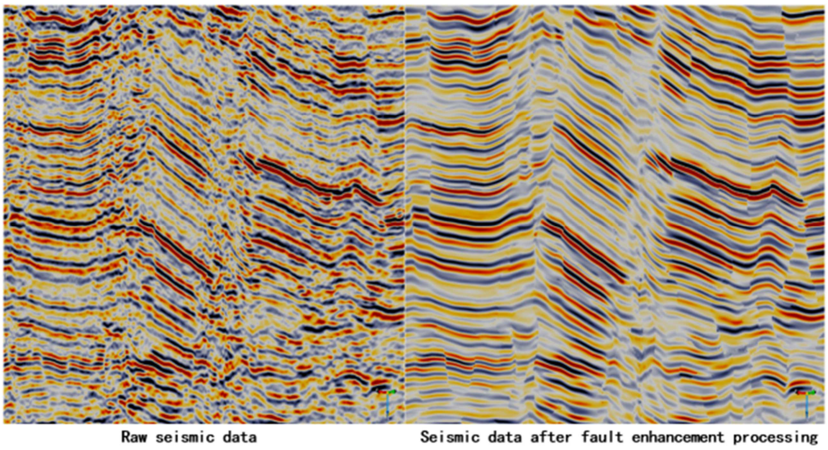


Figure 3. *Comparison of seismic data before and after interpretive processing.*

2.2. Artificial Intelligence Fault Interpretation

In recent years, with the rapid development of artificial intelligence, machine learning and deep learning techniques have been increasingly applied in the field of geophysics, and various algorithms based on convolutional neural networks (CNN) have been used for fault recognition. Chen Gui and Liu Yang (2020) summarized the methods of fault recognition based on artificial intelligence and conducted a comprehensive analysis of the principles and advantages and disadvantages of different methods.

Currently, the mainstream artificial intelligence algorithms both domestically and internationally are mainly based on convolutional neural networks, such as CNN, fully convolutional neural networks (FCN), and deep convolutional neural networks (DCN). The U-net and 3D U-net++ convolutional neural network models are considered the mainstream research methods for automated fault recognition due to their high efficiency and accuracy. Figure 4 illustrates the mainstream artificial intelligence fault recognition, where different methods differ mainly in network structure, preprocessing, and post-optimization techniques.

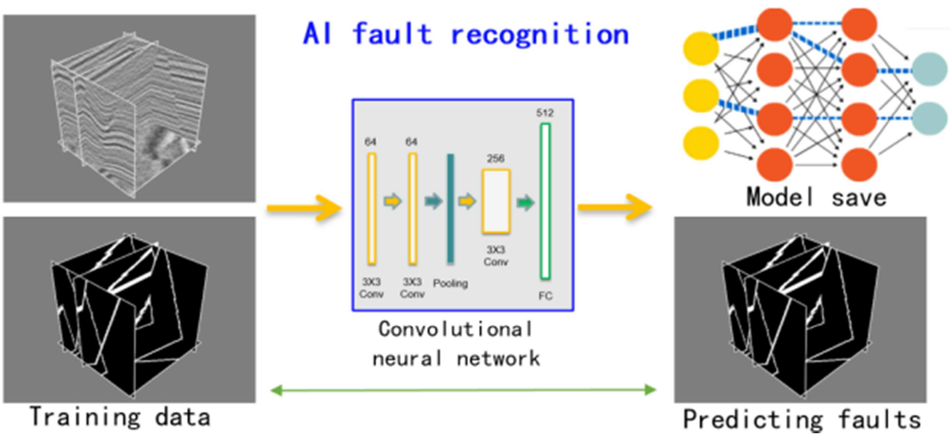


Figure 4. *Schematic diagram of artificial intelligence fault recognition.*

The convolutional neural network-based automatic fault recognition method consists of the following three core steps: The first step is the creation of synthetic seismic records and fault labels. The second step is the construction of the convolutional neural network architecture. The third step is the training and optimization of the convolutional neural network.

Due to the limited availability of trained model samples for AI fault recognition or their potential ineffectiveness in specific work areas, it is necessary to introduce transfer learning to improve the accuracy and reliability of fault recognition. By training the convolutional neural network on a large number of synthetic fault samples, and then fine-tuning the network using a small number of manually labeled actual fault samples, transfer learning enables the network to learn more actual fault features. This greatly reduces the occurrence of missed detections and false detections, thereby improving the accuracy of fault recognition. Figure 5 illustrates the workflow of the artificial intelligence fault interpretation technique summarized in this study.

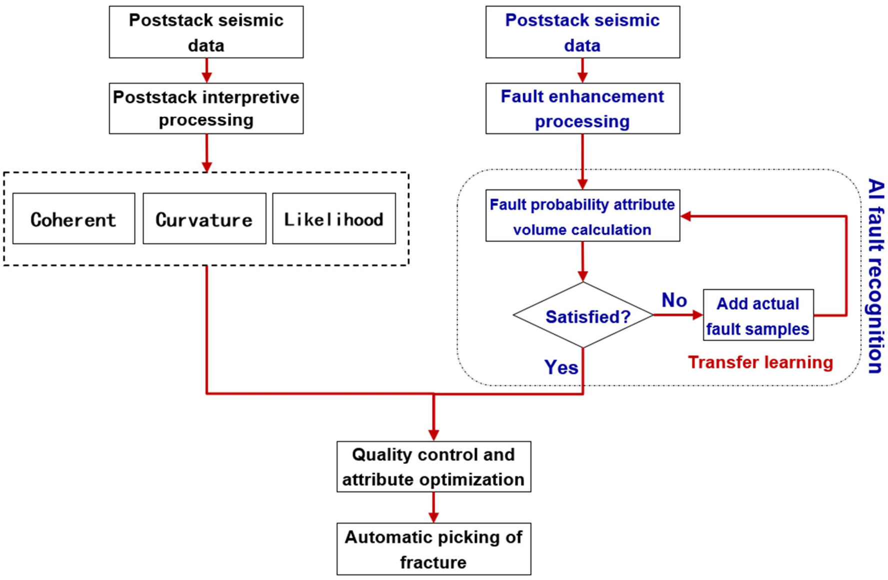


Figure 5. *Artificial Intelligence Fault Recognition Technology Workflow.*

3. Technical Application Effectiveness

The Sichuan Basin is characterized by the development of strike-slip faults, and numerous drilling activities have shown that high-yield gas is often associated with these faults, indicating a close relationship between strike-slip faults and hydrocarbon accumulation. This study focuses on the BD1 block to conduct interpretive processing and research on low-level sequence fault interpretation using artificial intelligence, and to develop an effective and rational workflow for artificial intelligence-based strike-slip fault interpretation. This aims to improve the accuracy and efficiency of fault recognition and provide a favorable basis for target selection.

Comparing the results of fault recognition between artificial intelligence and traditional methods in the target layer of the study area (Figure 6), it can be observed that traditional attributes (coherence, curvature, maximum likelihood) can indicate the location of faults to some extent. However, certain fault locations in seismic data may not exhibit discontinuous features, making it difficult for traditional methods to obtain clear and continuous fault detection results. Artificial intelligence-based fault detection results surpass all traditional attributes in terms of continuity, noise resistance, accuracy, resolution, and computational efficiency.

Artificial intelligence technology demonstrates significant advantages in profile fault imaging, subtle fault imaging, and deep noise resistance.

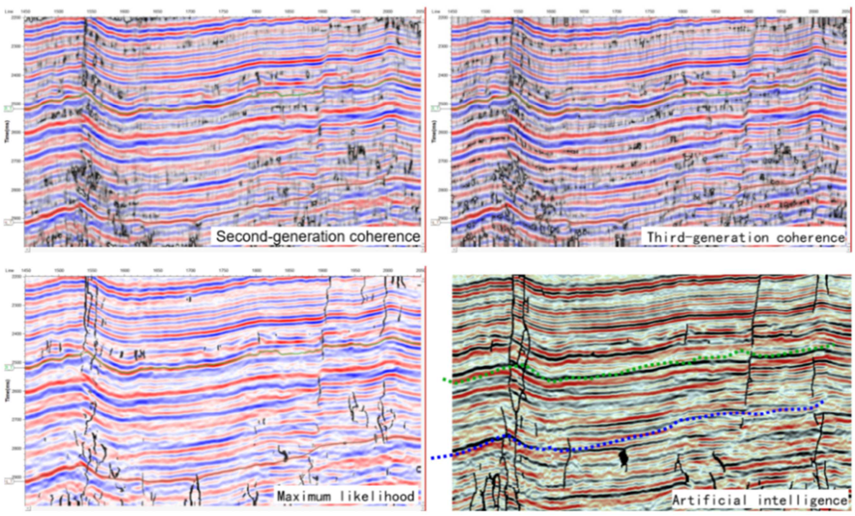
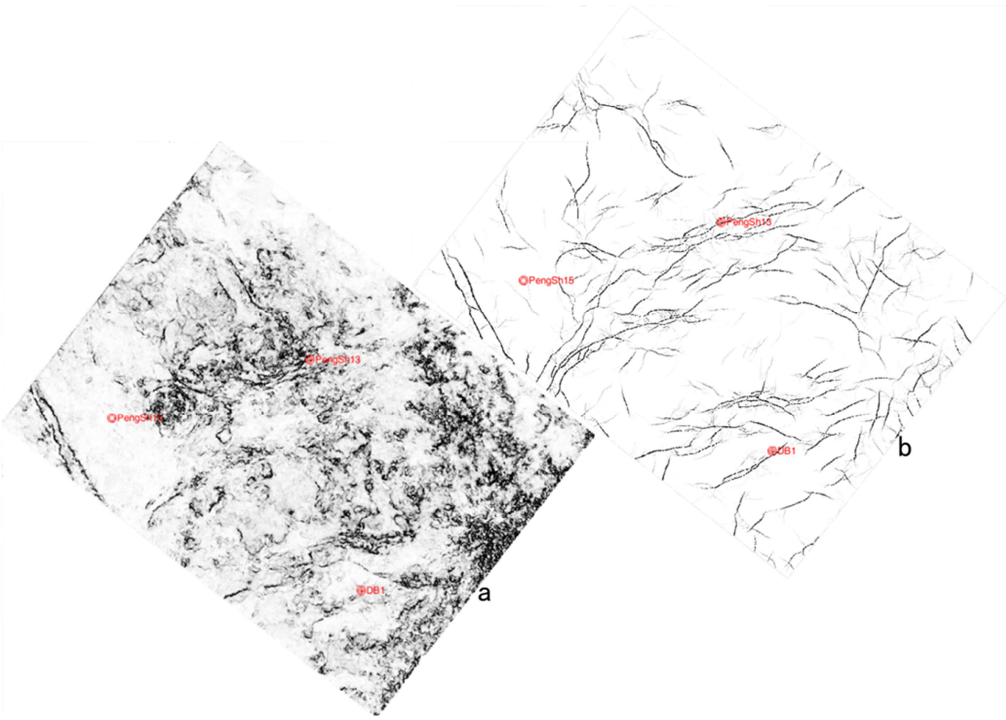


Figure 6. *Comparison between Artificial Intelligence Fault Recognition and Traditional Fault Recognition Methods.*



a. Coherence attributes b. Artificial intelligence fault probability volume

Figure 7. *Comparison between Traditional Coherence Attribute Plane and Artificial Intelligence Fault Recognition.*

Figure 7 shows the comparison between the artificial intelligence fault probability volume (Figure 7a) and the coherence attribute (Figure 7b) for the basement boundary of the Cambrian system. From the Figure, it can be observed that artificial intelligence technology has significant advantages over traditional methods in terms of profile fault imaging, subtle fault imaging, and deep noise resistance. The AI fault interpretation exhibits clearer spatial distribution characteristics and better combination relationships.

Figure 8 compares the results of artificial intelligence fault recognition using a dataset of 100,000 samples and a dataset of 1,200 samples. It can be seen from the figure that the larger sample dataset enables higher precision imaging of faults, resulting in more accurate and reasonable fault recognition compared to using a smaller sample dataset.

By establishing discriminative criteria based on artificial intelligence parameters, multiple scales of faults can be characterized. Figure 9 shows the results of multi-scale fault recognition. In the Figure, the red color corresponds to large-scale faults, black represents medium-scale faults, and blue represents small-scale faults. After completing the artificial intelligence fault interpretation, the fault attribute volume is optimized, and automatic extraction of fault planes is performed according to the requirements of different scale geological targets.

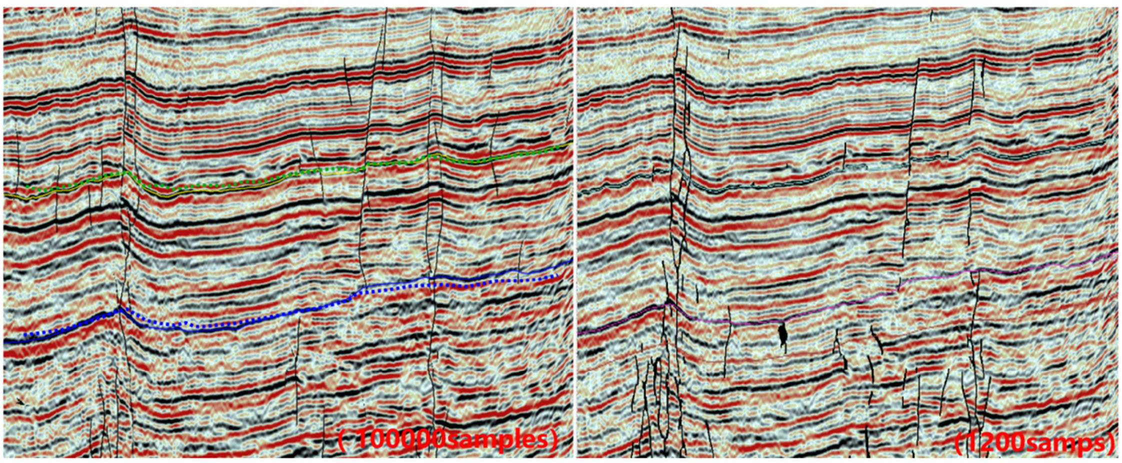


Figure 8. *Comparison of Artificial Intelligence Fault Recognition Results from Different Models.*

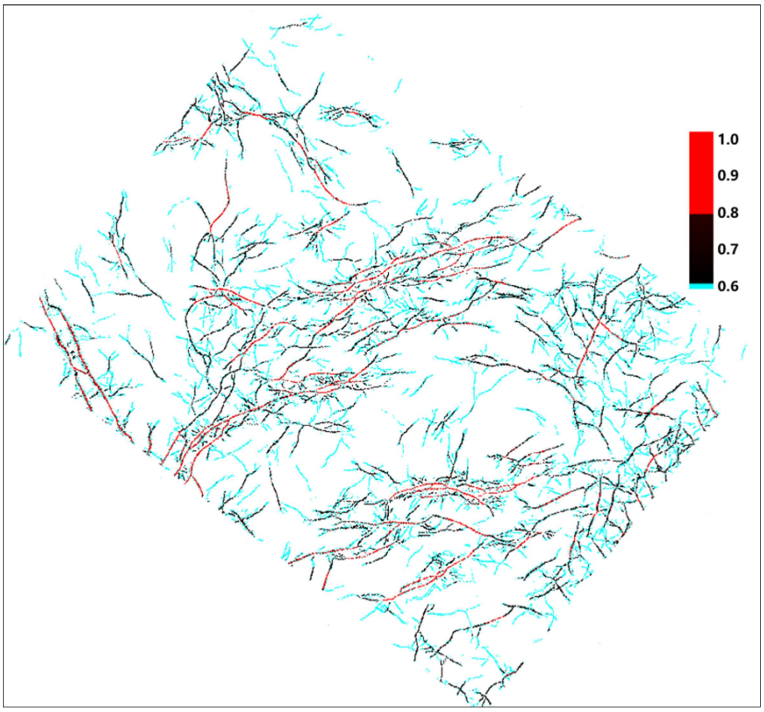


Figure 9. *Artificial Intelligence Multi-scale Fault Classification and Characterization.*

4. Conclusions

The combination of methods such as dip scanning, structure-guided filtering, edge-preserving filtering, and band-pass filtering is necessary for the artificial intelligence-based low-rank fault identification in seismic data. It can enhance the fault features, improve the signal-to-noise ratio of seismic data, and optimize the dominant frequency band for small faults, thereby further improving the ability to identify small faults.

Low-rank faults and strike-slip faults have small displacements and short extensions, making them difficult to identify using traditional attributes such as coherence, curvature, ant tracking, and maximum likelihood attributes due to noise interference. However, artificial intelligence fault interpretation techniques can quickly and effectively characterize the spatial distribution characteristics of low-rank faults, significantly improving the accuracy and efficiency of fault interpretation.

The difficulty in obtaining a large number of fault samples for artificial intelligence networks makes it challenging for prediction models to meet the recognition requirements of different types of faults. Therefore, it is necessary to introduce transfer learning strategies and incorporate actual fault samples to enable the network to learn more real fault features. The application results have shown that the network after transfer learning can significantly reduce cases of missed and misidentified faults, thereby improving the accuracy of fault recognition.

The key to improving the accuracy of artificial intelligence-based low-rank fault identification lies not only in the model itself but also in the sufficiency, uniform distribution, and representativeness of the samples. These factors need to be taken into account and given due attention.

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Biography

Zhang Sheng (1979-), Male, Master's degree, Senior engineer, Mainly engaged in comprehensive research on reservoir geophysics.