Convolutional neural network microseismic event detection based on variance fractal dimension

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Abstract—Microseismic event detection helps to predict outbreak catastrophic problems and has essential applications in resource exploration. Low SNR microseismic signal detection is a challenging task in microseismic detection. In this paper, we propose a (convolutional neural network microseismic detection method based on variance fractal dimension) VFD-CNN method based on the variance fractal dimension (VFD). In this method, signals and background noise are first measured by variance fractal dimension, which can effectively extract seismic nonlinear features. These fractal features are then fed into VFD-CNN to distinguish signal and noise. Finally, the variance fractal dimension of the test data is fed into the optimal model to detect microseismic events. The VFD-CNN method can significantly improve the detection capability of low SNR microseismic signals. To verify the performance of the VFD-CNN method, We use the VFD-CNN method to synthesize microseismic data. Furthermore, the comparison experiments were conducted using VFD-CNN and short-term averaging to long-term averaging (STA/LTA) algorithms. The results show that the VFD-CNN method can significantly improve the detection of low SNR microseismic signals, and its precision is substantially higher than the STA/LTA algorithm.

1. Introduction
During hydraulic fracturing technology, the energy generated by hydraulic fracturing is usually weak [1]. Therefore, the weak signals are easily drowned by the background noise, this has made the detection of microseismic events a challenge. Because fast and accurate detection of microseismic events is the basis for later microseismic data processing, it is essential to detect microseismic events before locating the source and analyzing the mechanism. The timely and accurate detection of microseismic events in tunneling, underground grouting, and mineral mining can overhaul the project's processing in advance and make safety issues more accurately prevented. An accurate detection method for low SNR microseismic events is necessary. The energy analysis method is the main tool for microseismic event detection [2],[3], which include (Allen, 1978; Hildyard et al., 2008, Khadhraoui et al., 2010), polarization analysis (Jurkevics, 1988), artificial neural networks (Zhao and K. Takano, 1999; Li et al., 2013), fuzzy logic theory (Chu and Mendel, 1994), higher-order statistics (Kuperkoch et al., 2010) and Akaike information criterion (AR-AIC) (Sleeman and Van Eck, 1999. Leonard, 2000; Andy, 2011). Maeda (1985) enhanced the AR-AIC approach by utilizing seismic recordings to derive the AIC function values directly without computing the AR coefficients, dubbed the VRA-AIC method. Various
microseismic detection methods have been presented in recent years. Huanlan Zhang et al. proposed a two-step method for microseismic first-to-pickup based on the time-window energy ratio and AIC[4]. Shang et al. proposed several first-in methods based on STA/LTA [5], AIC, and the signal's skewness and kurtosis, these algorithms are suitable for signals with low SNR. However, there are several disadvantages to the semi-automated detection approach. It requires a careful setting of parameters. Furthermore, because these algorithms are sensitive to abrupt amplitude increases, noise with an energy equal to or higher than that of a microseismic event can be identified as a signal.

In this paper, we propose a convolutional neural network microseismic detection method based on variance fractal dimension to improve the detection capability of low SNR microseismic events, while eliminating the threshold setting problem traditional algorithms. We investigate the powerful feature expression capability of variance fractal dimension for microseismic data, we also investigate the powerful feature extraction and classification capabilities of convolutional neural networks. We train, validate, and test the method by simulating microseismic data and fully demonstrate that the current method outperforms the benchmark algorithm.

2. Description of the method

2.1. Workflow diagram
The workflow of this method is shown in Figure 1. The workflow diagram consists of three steps:
- First, calculate the variance fractal characteristics of the sample.
- Then, input the variance fractal characteristics of the sample into the convolutional neural network model. Classify the signal and noise through the convolutional neural network and obtain the final classification model.
- Finally, Calculate the fractal dimension of the variance of the test data. Cut fractal data into a series of small samples by sliding window operation, Sliding window size is the training set sample size. A series of small samples are fed into the model to complete the prediction.

Output the probability that all samples are identified as signals, When the probability is greater than 0.5, it is considered a microseismic event.
2.2. Variance fractal dimension

Fractal dimension analysis relies on the self-similarity or self-similarity of multi-scale objects, and its basic idea is based on Brownian motion (Grieder, 1996). Fractal dimension, unlike Euclidean geometric dimensions, reflects the validity of irregular forms occupying space, because in fractal theory dimensions can be all positive real numbers, and variance fractal dimensions are more strongly characterized than the "roughness" of the original microseismic data. VFD is a special class of fractal calculus[6],[7]. A time series is represented by E(t). The relationship between the Variance \[\text{Var}(E(t_i + n\Delta t) - E(t_i))]\ and the time scales \(n\Delta t\) satisfies the power law

\[
[\text{Var}(E(t_i + n\Delta t) - E(t_i))] \propto |n\Delta t|^{2H}
\]

(1)

Where the \(H\) is called the Hurst exponent and is constrained in between 0 and 1. the Hurst exponent \(H\) is calculated using the following equation

\[
H = \lim_{\Delta t \to 0} \frac{\log[\text{Var}(E(t_i + n\Delta t) - E(t_i))]}{\log((n\Delta t)^2)}
\]

(2)

The VFD \(D_\sigma\) is determined by the Hurst exponent \(H\) and embedding dimension, For one-dimensional microseismic data, the \(G\) is equal to 1. and their relationship is given by

\[
D_\sigma = G + 1 - H
\]

(3)
This gives the fractal dimension of the variance at time $t_1$. The fractal dimension of the variance of the whole microseismic data is obtained by applying it to the entire curve. The original data and the calculated fractal dimension data are shown in Fig. 2. The fractal dimensions in the noise and signal segments show different characteristics. Therefore, the variance fractal dimension of seismic can characterize the microseismic and distinguish the signal from the noise.

![Fractal feature extraction](image)

Fig. 2 Fractal feature extraction

2.3. CNN Structure

Detecting microseismic events distinguishes noisy data and signal data, which is essentially a binary classification. As a kind of supervised deep learning, the convolutional neural network has higher performance and lower computational complexity due to its unique convolutional layers and weight sharing characteristics, which makes feature extraction more accurate. We choose a one-dimensional convolutional neural network for feature extraction and classification of data[8].

The convolutional neural network is implemented to deal with a nonlinear inverse problem by interactive forward propagation and backward propagation. The features are extracted by the network designed in forwarding propagation and the updated parameters to make the classification, and the backpropagation aims to update these parameters. The detailed implementation process of the convolutional neural network is described in detail in many kinds of literature. The forward propagation mechanism of the convolutional neural network is shown in the equation

$$x_j' = \beta(\alpha_j') = \beta(\sum_{i \in M_j} x_i'^{-1} \otimes W_j' + b_j')$$

(4)

The final layer applies the softmax exponential function to output the probabilities

$$p(Y = i \mid x) = \frac{e^{\alpha_i(x)}}{\sum_{j=1}^{2} e^{\alpha_j(x)}}$$

(5)

The loss function we choose is the cross-entropy loss function

$$L = \frac{1}{N} \sum_{i} [-y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

(6)

For one-dimensional time series of microseismic data, we choose a one-dimensional convolutional neural network. According to the classical convolutional neural network structure, we build the overall convolutional neural network structure as shown in Figure 3, using four convolutional layers, two fully connected layers one output layer.
The parameters of each layer are shown in Table 1.

| Network layer | Number of filters | Filter size/Step length | Activation function |
|---------------|-------------------|-------------------------|---------------------|
| Conv layer 1  | 256               | 5/1                     | ReLU                |
| Conv layer 2  | 128               | 5/1                     | ReLU                |
| Conv layer 3  | 64                | 5/1                     | ReLU                |
| Conv layer 4  | 32                | 5/1                     | ReLU                |
| FC layer 1    | 128               |                         | ReLU                |
| FC layer 2    | 64                |                         | ReLU                |
| Output layer  | 2                 |                         | Softmax             |

2.4. Evaluation indicators

We define the following, the signal correctly identified as a signal is defined as TP, the signal not detected is defined as FN, the noise is misidentified as a signal is defined as FP, and the final trained model is evaluated using the precision, recall and F1 scores. In the discipline of deep learning classification, these three evaluation metrics have established the standard. Precision is defined as follows:  
\[ \text{Precision} = \frac{TP}{TP + FP} \]  
Recall represents the proportion of correctly detected events relative to the number of real events and is calculated by:  
\[ \text{Recall} = \frac{TP}{TP + FN} \]  
The F1 score [9] evaluates the combined performance of the algorithm, which is the harmonic mean of accuracy and recall  
\[ F1 = 2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \]  

3. Experiment

We construct the training and validation sets by synthesizing simulated microseismic data. First, we synthesize 2000 channels of microseismic data with SNR of -10 dB, each channel contains 2 events, each event contains 900 sampling points, intercept 4000 complete microseismic events and 4000 sampling points for 900 noise, and then calculate the variance fractal dimension of each of the 8000 samples to form the final training set and validation set. The SNR, a key indicator of the quality of the data is given by  
\[ \text{SNR} = 20 \times \log_{10} \left( \frac{A_{\text{signal+noise}}}{A_{\text{noise}}} \right) \]  
where,  
\( A_{\text{signal+noise}} \) and  
\( A_{\text{noise}} \)  
is the root-mean-square (RMS) amplitude of the microseismic record and the noise record, respectively.

The fractal dimension samples of signal samples and noise samples are shown in Fig. 4 Sample data,
(a) and (b) are the original signal samples and the signal samples after calculating the fractal dimension, (c) and (d) are the original noise samples and the noise samples after calculating the fractal dimension.

After training the model, we synthesized 200 microseismic data with SNR of -12 dB, -16 dB, and -20 dB to test the performance of the model, and the test results are shown in Figure 5. Figures (a) to (d) show the detection results of microseismic events at an SNR of -12 dB. All 200 microseismic test events were detected correctly without any false detections or missed detections. (e) to (h) are the detection results of microseismic events with the SNR of -16 dB, with a few false detections and very few missed detections among the 200 events; Figures (i) to (l) are the detection results of microseismic events with the SNR of -20 dB, with most false detections and a few missed detections among the 200 events.
To evaluate the proposed method, we calculate the precision, recall and F1 scores based on the test data sets of different SNR, and compare the proposed method with STA/LTA, which is considered to be the most common method for seismic and microseismic detection tasks, by F1 scores. The parameters of STA/LTA are set according to the optimal values in the literature.

From the evaluation metrics for different SNR in Figure 6(a), it can be concluded that microseismic events can be detected almost wholly when the SNR is already relatively low at -12 dB. In contrast, all three metrics drop when the SNR is -16 dB, but are still at a high level of over 95%. As the SNR continues to drop to -20 dB, the precision drops to 61%, because most of the events are still detected correctly so that the recall rate can still be maintained at 90%. In Fig. 6(b), we compare the proposed method with STA/LTA using the F1 score as the evaluation index. Our proposed method outperforms the benchmark STA/LTA at -16 dB and -20 dB in terms of positive detection, false detection, and missed detection, which is well reflected in the F1 score of the valuation index.
4. Conclusion
This paper proposes a deep learning microseismic event detection method based on variance fractal dimension, which combines variance fractal dimension with deep learning. The nonlinear features are extracted by calculating the variance fractal dimension of microseismic signals and noise. The seismic variance fractal features are fed into a convolutional neural network for signal and noise classification. The method is tested with simulated data. By calculating three evaluation metrics and comparing them with currently available methods, it is concluded that VFD-CNN has better performance than the benchmark algorithm STA/LTA. Reducing the false detection rate for microseismic events with lower SNR is necessary for future work.

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References
[1] Chu Fangdong, JIAO Yajun, YANG Lifeng, et al. Natural fracture identification at hydraulic fracturing wells with microseismic[J]. Oil Geophysical Prospecting, 2018, 53 (S2): 143-147.
[2] R. V. Allen, “Automatic earthquake recognition and timing from single traces,” Bulletin of the Seismological Society of America, vol. 68, no. 5, pp. 1521–1532, 1978.
[3] R. Allen, “Automatic phase pickers: Their present use and future prospects,” Bulletin of the Seismological Society of America, vol. 72, no. 6B, pp. S225–S242, 1982.
[4] Y. Long, J. Lin, B. Li, H. Wang, and Z. Chen, “Fast-AIC method for automatic first arrivals picking of a microseismic event with multitrace energy stacking envelope summation,” IEE Geosci. Remote Sens. Lett., vol. 17, no. 10, pp. 1832–1836, Oct. 2020.53 (S2): 143-147.
[5] Liu H, Zhang J. STA/LTA algorithm analysis and improvement of Microseismic signal automatic detection. Progress in Geophysics (in Chinese), 2014,(4):1708-1714.
[6] L. Jiao and W. M. Moon, “Detection of seismic refraction signals using a variance fractal dimension technique,” Geophysics, vol. 65, no. 1, pp. 2000.286–292.
[7] M.N.A.Shaon, K.Ferens, and M.Ferens,” Wormhole attack detection in wireless sensor network using variance fractal dimension,” in Proceedings of the International Conference on Security and Management (SAM). The Steering Committee of The World Congress in Computer Science, Computer….2016,p.22.
[8] Ross, Z. E., M.-A. Meier, and E. Hauksson (2018). P-wave arrival picking and first-motion polarity determination with deep learning, J. Geophys. Res. 123, no. 6, 5120–5129.
[9] T.-L. Chin, K.-Y. Chen, D.-Y. Chen, and D.-E. Lin, “Intelligent real-time Earthquake detection by recurrent neural networks,” IEEE Trans. Geosci. Remote Sens., vol. 58, no. 8, pp. 5440–5449, Aug. 2020.