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Fractal Characteristics of the Spatial Distribution of Mine Earthquake Sources in the Vicinity of a Fault: A Case Study in the Ashele Copper Mine

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Abstract: Potential faults are common sensitive geological bodies that affect the safe mining of underground mines, often leading to major accidents such as rock instability and rockburst during mining. The failure mechanism of faults has been widely studied. However, due to the spatiotemporal specificity of fault occurrence, there are few theoretical and mathematical methods suitable for effective analysis in mine safety risk management. This study aims to introduce fractal theory to characterize the spatiotemporal activity fractal characteristics of induced faults intersecting the mining site and roadway during the mining process of the Ashele copper mine in China. Using microseismic systems and fractal theory, a spatiotemporal fractal model of the fault slip process is constructed, and a fractal analysis method is proposed. The fractal dimension value is calculated based on the spatiotemporal parameters of different segments and stages. The fractal dimension is used to characterize and analyze the evolution of the fault. The physical formation process of potential faults and the relationship between fractal dimension values and multiple parameters, including spatial clustering, regional distribution characteristics, and energyrelease characteristics, were analyzed based on the division of events into different time stages. Discovering fractal dimension's temporal and spatial-temporal characteristics can provide technical references for mine disaster prevention.

Keywords: fractal dimension; spatial distribution; potential minor fault; mine earthquake source

1. Introduction

Hard rock underground mines are prone to disasters [1–8], and indoor tests combined with onsite online monitoring are often used to control damage in real time [9–11]. In the processes of underground mining, microseismic monitoring can reproduce destruction events that are caused by faults [12], fracture zones [13], and rock surroundings [14]. Lab-based acoustic emission tests can also achieve good monitoring effects [15]. However, the timeliness of recurrence is difficult to predict by analyzing and judging damage trends [16,17]. In addition, the distributions of microseismic events are not uniform and the spatial characteristics are difficult to characterize [18]. The fractal theory has been widely evaluated to achieve a better understanding of the spatiotemporal laws of dynamic damage, such as potential faults, and has been used to quantitatively characterize disasters in the mining field [19-21].



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Fault-related microseismic activity in mines has been extensively studied. Henderson et al. [22] linked the b values with the fractal dimensions of sources and described a group of mine earthquake events in a fault zone. The events were divided into multiple spatial clusters, and the correlation between the two parameters was analyzed within the clusters. They found that the correlation could be related to void crack growth. Leśniak and Isakow [23] installed four triaxial sensors in a coal mine for monitoring and described the development characteristics of panel faults using mine earthquake event clusters. An evaluation function based on event energy and time interval has also been established to evaluate the relationships between specific clusters and high-energy events. Cheng et al. [24] and Xia et al. [6] studied the fault activation characteristics of mines. According to the distance between the fault and the longwall working face, the fault activation process can be divided into four stages. The b value decreases the closer the longwall working face is to the fault, indicating that the stress around the fault has been redistributed. Mendecki et al. [25] systematically classified mining earthquake data recorded near the fold of a mine according to the fault mechanisms. They described the stress redistribution process around the fault during mining and used it to study the trigger mechanisms of microseismic events. Liu et al. [26] took the east area of the Jinshandian Iron Mine as the engineering research background and adopted geological survey, microseismic monitoring, numerical simulation, and theoretical analysis methods to examine the ground pressure manifestation laws of metal mines under the influence of geological structures, such as faults. Chen et al. [27] analyzed the destruction and connection of a shale gas field using microseismic monitoring, mainly using the spatiotemporal evolution laws of microseismic events to explore the migration dynamics of fluids. They then summarized the relationships between b and d values and different event clusters to measure the complexity of the faults and fractures.

Combining fractal theory and microseismic monitoring is becoming increasingly common. Fractal theory is one of the three theoretical frontiers of nonlinear science and is a powerful tool for characterizing the large number of irregular and non-smooth geometric bodies that exist in nature. It provides possibilities and a basis for people to understand the whole from the parts and the infinite from the finite. Using fractal geometry and damage mechanics, Xie and Pariseau [28] investigated the microseismic features of rock bursts and discovered that the geographical distributions of microseismic events exhibited fractal clustering patterns. The fractal dimensions were typically much smaller in the vicinity of rock bursts, providing a theoretical foundation for catastrophe prediction. Mondal et al. [29] conducted a fractal analysis on the distribution patterns of seismic data activities and discovered that changes in multifractal spatial seismic activities were significantly associated with highway roof collapse, which could provide a reference for mine roof fall catastrophe prediction. Zhao et al. [30] researched the laws between fractal dimensions and rock mass failure activities based on fractal theory. The box dimension calculation method has been used to analyze microseismic event information from the Ashele Copper Mine and the relationships between its spatiotemporal distribution laws, production activities, and development projects have been analyzed using clustering. Rock mass failure can be successfully predicted. Mao et al. [31] studied the Baihetan Hydropower Project and revealed the characteristics of early warning signals in rock fracture microseismic information. This research showed that the rock microfractures showed certain multifractal time-varying response characteristics before the slope cracks increased, which could be used as deformation warning signals. However, in the above-mentioned research, the application of fractal theory in mining engineering practice is relatively limited [32]. In particular, the acoustic emission experiments in the laboratory are very limited, so we

introduce fractal theory to conduct cutting-edge analysis and research on the process of mine fault rupture.

To deepen our understanding of mining-induced fault failure laws, we studied the development processes of potential faults near the middle section of the Ashele Copper Mine in Xinjiang, China, especially spatiotemporal parameters, which were obtained using a microseismic monitoring system. Using a three-dimensional fractal analysis framework model, we analyzed and calculated the corresponding relationships between fractal dimensions and intermediate segments, the number and frequency of events, and the radiation energy during different periods.

The results showed that the development and destruction of potential small faults were closely related to staged ore body mining. In general, the faults presented the characteristics of a non-uniform periodic time series, and the shape of the oblate ellipsoid was distributed and concentrated in space. Focusing on the relationships between the development processes of minor faults and the fractal characteristics of microseismic events, we found that the fractal characteristics of the spatiotemporal seismic parameters of the sources allowed for dynamic analysis of disasters.

2. Engineering Site and Microseismic Monitoring

2.1. Project Location Summary

Figure 1a depicts the Ashele Copper Mine, which is located in the north of Xinjiang, China, and Figure 1b shows its surface morphology. It has rich copper resources (discovered in 1986 and proven in 1992) and it is the second-largest copper mine in China [33]. The mine contains pyrite-type copper and a zinc polymetallic deposit that originated from volcanic eruption sediment [34,35]. This determined the main mining scales and methods at the Ashele Copper Mine. Figure 1a shows that Ashele Copper Mine, which is located in the north of Xinjiang, China, and Figure 1b shows its surface morphology. It has rich copper resources (discovered in 1986 and more extensively analyzed in 1992) and it is the second largest copper mine discovered in China [33]. The deposit from mines contains pyrite-type copper and a zinc polymetallic deposit that originated from the sediment created during a volcanic eruption [34,35]. This determines the main mining scales and methods used within the Ashele Copper Mine.

In 2019, a research project was carried out near the middle of a certain mining level in the second phase of the Ashele Copper Mine. The main purpose of our investigation was to examine the occurrence and failure process characteristics of potential faults that were induced by mining. The Ashele Copper Mine is characterized by a steep dip, short strike, and large horizontal thickness; therefore, the large-diameter deep hole and the subsequent medium–deep hole-filling mining methods have been adopted there.

During mining processes, the overall stability of the upper and lower wall rock mass is poor due to the development of joints and fissures. The ground pressure is also becoming more prominent. The supported roadway is seriously deformed, and deformation of the local roadway walls, floor heave, roof collapse, surrounding rock brittleness, abnormal sounds, and even weak rock bursts phenomena, such as catapults and caving, occurs many times during deep excavation projects.

To reproduce and analyze the potential small faults in the target area, we delineated the target area using the microseismic monitoring system that has been built in the Ashele Copper Mine, as shown in Figure 1c,d.



Figure 1. The mine location, landform, microseismic monitoring topology system, and underground system. (a) geographical location; (b) topographic features; (c) development Engineering and Microseismic Monitoring; (d) topological structure.

Figure 2 shows the layout of the target area and the monitoring network, which mainly includes three middle floors and microseismic monitoring sensors arranged within the space. In the figure, the blue circles indicate the locations of the microseismic monitoring sensors, the green line represents the +300 m middle section roadway, the blue line represents the +350 m middle section roadway, and the purple line represents the +450 m middle section roadway.



Figure 2. The layout of the target area and monitoring network: (a) stereo diagram; (b) top plan view.

It was preliminarily speculated that when a local stope was in the vicinity of a potential minor fault, the microseismic events near the fault would show ellipsoid spatial distributions. To analyze and evaluate the processes in detail, we selected mine earthquake activities in specific areas within the microseismic monitoring system for monitoring and analysis.

2.2. Monitoring Network

A total of 23 single-axis speed sensors and 3 three-axis speed sensors were installed in this project. The sensors used were GU(T)-10 models manufactured by Hubei Seaquake Technology Co., Ltd. (SSS), Wuhan, Hubei, China. The sensitivity was 100 V/m/s (\pm 5%). The coil resistance was 4000 Ω (\pm 5%). The frequency range was 10~1000 Hz (\pm 10%). The measurable range was 10~2000 Hz. The size of the single-axis sensors was 33 mm × 120 mm, while the three-axis sensors were 58.5 mm × 180 mm.

Figure 3 shows the layout positions of the sensors in the different middle levels and the sensor distribution near the middle level in elevation. The sensors were distributed at the main safety points of the footwall roadway and hanging wall roadway at cross intervals along the ore body strike. There was a certain height difference in the horizontal distribution of each middle level. There was also a large elevation difference in the different middle-level heights. The figure generally presents the envelope of the ore body and the main mining area and the green, blue, magenta and red spheres represent the sensor positions on the middle +500 m, +450 m, +350 m, and +200 m levels, respectively.



Figure 3. The relationships between the positions of the microseismic monitoring sensors and the middle levels in the study area. (**a**) +450m middle and its microseismic events.; (**b**) +350m middle and its microseismic events.; (**c**) +300m middle and its microseismic events.

All sensors were recoverable sensors that were fixed into boreholes so that they could fully couple with the rock mass. The sensor cables were laid down from the surface through the main roadways and shafts. A new-generation high-precision multichannel intelligent microseismic monitoring remote control system was installed in the ground control room to monitor for rock fractures. This intelligent monitoring system effectively filtered out environmental noise, which enabled the data acquisition system and source positioning system to operate accurately and normally. Microseismic data were recorded continuously at a 2000 Hz sampling rate.

In this study, we analyzed mining earthquake data from 1 July 2019 to 31 May 2020. During the 11-month monitoring period, the progress of a stope around a potential small fault was as follows: the stope first advanced from the south to the nearest point of the small fault and then advanced from the near point of the small fault to the north. Entire mining processes were accompanied by small faults and surrounding microseismic events, which were scattered uniformly.

3. Microseismic Data and Fractal Processing Method

Combined with MATLAB 3D model reconstruction, simulation analysis, and fractal theory, we employed the spatiotemporal fractal analysis research method for the mine earthquake sources, based on microseismic event information. As shown in Figure 4, the spatiotemporal parameters of the potential small faults and microseismic events were reconstructed and inversed using MATLAB R2018a, and a cyclic iterative quantitative analysis was carried out.



Figure 4. A flow diagram of the research method and fractal dimension analysis.

In addition, based on the model we constructed using our fractal dimension analysis, the fractal dimensions of each micro-unit in the study area were calculated. We simulated the fractal dimension values and their field distributions. The relationships between the evolution of small faults and the fractal dimensions of the spatial distributions of microseismic events could then be further studied. A detailed analysis and discussion are presented below.

3.1. Monitoring Data from the Mine

In this research project, all the microseismic events in the study area from 1 July 2019 to 31 May 2020 were acquired for preprocessing analysis. We analyzed 1720 rock fracture events, which were collectively referred to as mine earthquake events. At the same time, within the whole set of time series data, all 1720 mine earthquake events were distinguished according to event clustering and spatial distribution differences, based on mining activities [36]. Then, specific events near potential minor faults were screened. In the process of accurately evaluating microseismicity near the faults, we conducted a spatiotemporal clustering analysis [37–39] and employed the convolution neural network model method [12,40–42]. All microseismic event data were then preliminarily processed and analyzed. The results of the analysis were manually reviewed and screened to ensure that the near-fault events were accurately classified.

The frequency distributions of overall and local events during the 11-month monitoring period are shown in Figure 5. According to the frequency distributions and preliminary event trend analysis, the specific event dataset was divided into four stages (as shown in Figure 5b). Overall, the frequency of microseismic events gradually decreased. In the local near-fault events, there were quasi-periodic changes. This laid the foundation for the stage division and subsequent spatiotemporal fractal analysis.



Figure 5. The frequency distribution sand stage divisions of daily microseismic activities: (**a**) overall mine events; and (**b**) the distribution of microseismic events near mining-induced faults.

All events surrounding the generation, development, and end of potential faults are referred to as near-fault events. Their main parameters included the project ID, event date, event time, event X-axis coordinate, event Y-axis coordinate, event Z-axis coordinate, event radiation energy, PS wave radiation energy ratio, Richter magnitude, seismic moment, apparent stress, apparent volume, corner frequency, source radius, and the number of triggered sensors. See Table 1 for detailed information about the event parameters.

No.	Date	Time	Microseis	mic Event Coo	ordinates (m)	Radiant Energy (J)	PS Wave Radiation Energy Ratio	Richter Magni- tude	Seismic Moment (N·M)	Apparent Stress (MPa)	Apparent Volume (m ³)	Corner Frequency (Hz)	Source Radius (m)	Number of Triggered Sensors (I)
			х	Ŷ	Z									
1	17 July 2019	11:23:42	217	536	432	125.89	0.58	1.2	$7.9 imes 10^8$	0.04	$3.4 imes 10^5$	240	29.2	4
2	18 July 2019	7:59:04	303	427	430	15.85	1.26	1.7	$3.2 imes 10^8$	0.02	$3.7 imes10^5$	254	30.1	5
3	20 July 2019	16:31:26	419	391	384	2511.89	1.12	0.6	$2.0 imes 10^9$	0.34	$9.6 imes10^4$	294	19.2	5
4	21 July 2019	13:09:23	325	449	411	1.26	1.11	2.4	$1.3 imes10^8$	0	$5.3 imes 10^5$	199	33.9	4
5	21 July 2019	23:48:24	308	431	373	251.19	1.38	0.8	$4.0 imes10^9$	0.02	$3.6 imes10^6$	284	64.5	5
6	3 October 2019	18:06:39	454	412	251	1995.26	1.16	0	$2.5 imes10^{10}$	0.02	$2.0 imes 10^7$	205	113.4	6
7	13 October 2019	16:46:13	269	429	374	251.19	0.64	0.1	$2.0 imes 10^9$	0.04	$8.8 imes10^5$	26	40.3	4
8	18 October 2019	18:35:30	264	468	378	3162.28	1.97	0.4	$5.0 imes 10^9$	0.17	$5.0 imes10^5$	240	33.4	7
9	11 November 2019	12:51:03	361	453	345	398.11	1.17	0.5	$1.3 imes10^{10}$	0.01	$5.7 imes 10^6$	91	111.1	6
10	29 December 2019	18:39:33	418	415	311	19,952.62	1.17	0.4	$5.0 imes10^{10}$	0.12	$1.9 imes10^6$	156	77	8
							:							
46	12 April 2020	8:13:36	319	440	368	31.62	1.71	1.6	$5.0 imes 10^8$	0.02	5.2×10^5	358	33.7	3
47	12 April 2020	10:36:36	319	447	332	10	1.54	1.6	$1.0 imes 10^9$	0	$4.9 imes10^6$	26	71.1	3
48	12 April 2020	11:38:42	387	385	283	3.98	1.11	1.8	$6.3 imes 10^8$	0	$6.2 imes 10^6$	269	77.2	3
49	22 April 2020	3:55:10	344	426	307	79.43	1.62	1.4	$6.3 imes 10^{8}$	0.04	2.6×10^{5}	90	26.7	3
50	22 April 2020	12:14:21	320	463	335	1258.93	0.85	0.4	$7.9 imes 10^9$	0.04	3.2×10^{6}	51	62.1	5
51	29 April 2020	21:27:44	298	465	308	31,622.78	1.09	0.5	$6.3 imes10^{10}$	0.13	$8.4 imes 10^6$	171	85.4	9
52	4 May 2020	22:50:23	305	458	351	100	1.06	-1.2	1.6×10^{9}	0.02	$1.2 imes 10^6$	385	45.2	3

Table 1. Table of seismic source parameters (near-fa	ult).
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Note: Excerpts from all development events near the fault in the target monitoring area.

3.2. Brief Spatiotemporal Distributions of Near-Fault Sources

Since there were so many overall events that were non-uniformly scattered within the overall monitoring range when the full size was selected as the model boundaries, the accuracy of the data analysis in local areas near faults was low. To accurately analyze and evaluate the spatial fractal characteristics of mine earthquake events near faults, we divided the events into four stages, as shown in Figure 5a.

Specifically, in terms of time, the first stage was from 17 July 2019 to 31 December 2019 (gray), the second stage was from 1 February 2020 to 22 February 2020 (pink), the third stage was from 1 April 2020 to 10 April 2020 (orange), and the fourth stage was from 12 April 2020 to 4 May 2020 (red). In terms of spatial distribution, the spatial distributions of specific monitoring areas are shown in Figure 6a. The volume was about 600^3 m³. The distribution of main near-fault events in three-dimensional space is shown in Figure 6b. The potential minor fault that was monitored was about 300 m in length, 200 m in width, and 250 m in depth. The main span was from the middle level of +200 m to the middle level of +450 m in the middle level of the mine development.



Figure 6. The distribution and location relationships of microseismic events in the four different stages. (a) overall situation; (b) Localized enlargement.

3.3. Fractal Theory, Method, and Model Construction

3.3.1. Fractal Theory

The fractal theory describes and studies the objective laws of things in terms of fractional dimensions [43–45]. It breaks through the traditional expression of integer dimensions and can describe the real states and essential attributes of things. Its results are more consistent with the essence of complex things. Fractology can reveal the laws behind complex phenomena, even despite disordered chaos and irregular forms. It can understand the whole from the local and the infinite from the limited [46]. Modern mathematics has provided a new method for solving nonlinear and disordered problems in rock mass engineering [47,48]. In the field of rock mechanics, fractal theory is widely used. There has been a great deal of research on joints and fissures [49]. This research has also gradually expanded to include rock mechanics and other fields [3,21,50,51]. In particular, researchers have tried to apply this theory to the analysis of the source space [52], source volume [53], and source energy [54] characteristics of mine microseismic information. This has provided a new idea related to the study of complex dynamic disasters in deep hard-rock mines. The limited data have shown that the sources of rock mass fracturing in mining engineering also follow certain spatiotemporal fractal laws. Therefore, we tried to apply fractal theory to the analysis of microseismic monitoring event clustering within mine engineering.

3.3.2. Analytical Methods

To simplify the analysis, the fractal analysis was initially carried out using the local stope as the research area. According to the purpose, method, and process of this study, we focused on the fractal analysis of the spatiotemporal elements of microseismic monitoring parameters. Considering the time division stages and the particularity of the spatial distributions, the box dimension fractal analysis method was adopted in this study. In a time series, a "box" is a time interval unit. In terms of time, the microseismic events were arranged according to the above-mentioned stage divisions and the time domains were divided into sub-segments with similar periodicity. The interval days were in turn taken as the stage duration. For 3D spatial coordinate data, the "box" is a cube micro-unit. In space, a single microseismic event was regarded as a point source and a three-dimensional distribution model of the microseismic events in the stope space within each fractal statistical period was constructed. The stope space was divided into several fully covered micro-units, each of which had a dimensionless size of *l*. The number of microseismic events in each micro-unit of each stage was counted as *N*(*l*).

According to the three elements of earthquakes, the principle of directness, and the importance of the fracture sources, we chose to use time stage division and spatial fractal statistics to analyze the microseismic event parameters, i.e., after the time series division, the small cuboid micro-units that were equal in scale to the maximum size of the model were divided into the 3D simulation framework. The microseismic event data were categorized according to divided time scale and their coordinates were enveloped, extracted, and counted.

Specifically, box dimension fractal analysis was the most appropriate method for solving these problems [55–57] and its principle basis is as follows:

$$D = \lim_{\epsilon \to 0} \frac{\ln N(\epsilon)}{\ln\left(\frac{1}{\epsilon}\right)} \tag{1}$$

where ε is the unit scale of the coverage element, $N(\varepsilon)$ is the statistical number of elements in the closed interval, and *D* is the box fractal dimension.

In the statistical cells after the grid division, we counted and calculated the lnN values and their respective $lnN(\varepsilon)$ and $ln\varepsilon$ values. Then, we performed data fitting to calculate the score dimension *D* and the fitting coefficient.

Specifically, the spatial elements were divided as follows:

$$\varepsilon(l) = \frac{L}{m}, (m = 1, 2, 3 \dots, M)$$
⁽²⁾

where $\varepsilon(l)$ is the scale length of the divided space micro-unit, *L* is the length of the simulation model area, *m* is the partition number, and *M* is the partition number when the maximum number of events in the minimum space unit is 1.

We used the principle of the least squares method for the linear fitting of the logarithmic ε and $N(\varepsilon)$ values. Finally, we could determine the value of *m* when the fitting degree was optimal, as well as the unit division scale of the spatial elements.

3.3.3. Model Building

According to the actual division stages, after defining the time statistical units, we estimated the fractal dimensions of the spatial distributions of the three-dimensional layers as follows: (1) firstly, we constructed the statistical unit boxes, with the unit length of *l*; (2) then, we transformed the different cell length values ε to form several corresponding small boxes; (3) next, we calculated the number of events in the small boxes *N*(ε); (4) then,

we repeated the transformation several times to obtain a series of ε - $N(\varepsilon)$ data; (5) finally, we plotted $ln(1/\varepsilon)$ and $lnN(\varepsilon)$. The slope, namely the fractal dimension, was calculated using the least squares method. The fractal dimensions obtained were recorded as *D*. The analysis and model framework of the spatial fractal dimension values are shown in Figure 7. Figure 7a shows the division process of the quasi-periodic time stages. Figure 7b shows a schematic diagram of the nested mine earthquake data, along with the divided grid model and circular solution. Figure 7c presents the analysis framework after the optimal nested model frame size was solved.



Figure 7. A 3D spatial fractal dimension representation frame model, based on the locations of the mine's earthquake sources. (a) Time scale division; (b) The nesting process of events and spatial units; (c) Nesting results of events and spatial units.

4. Analysis of the Spatiotemporal Fractal Characteristics of Near-Fault Microseisms

4.1. Spatiotemporal Evolution of Mining-Induced Microseismicity

4.1.1. Analysis of Temporal Elements

According to Figure 5, the time stage division was preliminarily analyzed. Table 2 shows the detailed time nodes and their parameters.

Time Stage	Stage I	Stage II	Stage III	Stage IV
Time division	From 17 July 2019 to 31 December 2019	From 1 February 2020 to 22 February 2020	From 1 April 2020 to 10 April 2020	From 12 April 2020 to 4 May 2020
Interval days	167	21	9	22
Duration days	167 (Stage 1)	220 (Stage 2)	268 (Stage 3)	292 (Stage 4)
Pictures of representative damage cases on-site				

Table 2. The time node division table.

The first stage was from 17 July 2019 to 31 December 2019. During this period, the occurrence cycle of events was relatively long and the distribution was extremely scattered. The incubation process of small events was slow. The frequency was relatively low. There was no obvious peak. The overall activity was relatively low, which meant that the initial stages of near-fault occurrence were gradually induced. The nearby stopes and roadways had fewer rock fractures and were less affected. We called this the initiation phase.

The second stage was from 1 February 2020 to 22 February 2020. During this period, the duration was significantly shortened. The event distribution was dense and the frequency increased. Then, there was a downward trend, indicating that the incubation process gradually strengthened and reached a relatively low peak. We called this the activity enhancement phase.

The third stage was from 1 April 2020 to 10 April 2020. During this stage, the number of event data increased suddenly. This period was the shortest. The frequency was the highest. The events were intensive. The mine earthquake activity was the strongest. The rock mass fractures at the study site were more obvious. In particular, there were 11 microseismic events on 7 April alone. This showed that mine seismicity reached a peak during this period and that the mining processes, locations, and potential minor faults reached a peak of mining unloading. We called this the peak activity stage.

The fourth stage was from 12 April 2020 to 4 May 2020. During this last stage, the frequency of events significantly declined and the event intensity reduced. The corresponding rock fracture phenomenon was very slight. We called this the activity weakening stage.

4.1.2. Analysis of Spatial Elements in the Time Series

Figure 5 indicates how all near-fault events were divided into stages. In total, 52 rock fracture events near the fault were screened out from the microseismic events. The threedimensional evolution of the rock mass fractures near the fault is shown in detail in Figure 8.

In the first stage, the spatial distribution of microseismic events was scattered and sparse. The overall distribution was 50° northwest and the distribution characteristics of the events increased in this direction. There were few events below the middle level of +350 m. The event distribution in the middle level above +350 m was slightly dense and showed a certain spatial density. There was an approximate connection between the two end pinch-outs, which could predict for near-fault connections and development.

In the second stage, the spatial distribution of microseismic events was relatively concentrated. On the whole, there was a trend of gradual nucleation on the plane and the events were more concentrated near the middle level of +350 m. The through connection was completed based on the first stage of the through connection. This was closely related

to the mining intensity and concentration of the middle level of +350 m. At the same time, the rock mass fractures had the obvious trend of expanding toward the interior of the nucleation.



Figure 8. The distributions of the microseismic events around mining-induced faults in the four time stages.

In the third stage, the microseismic events showed a more intensive linear distribution in space. In the beginning, it was calm and no incidents occurred. Then, suddenly, the number of events increased sharply and microseismic events occurred at the same location in two directions at high speed. They showed strong linear development and surface agglomeration. At the same time, these events were closely connected to the events in the first two stages.

In the last stage, the spatial distribution of microseismic events spread linearly to the surface. As the mining was further away, the mining intensity gradually decreased. A high-strength failure in the third stage of the fault was transformed into a slow "tear", forming a tensile failure between fault planes that gradually weakened. Finally, no events occurred near the fault and the potential mining-induced small fault completed its development process.

4.2. Gridding Analysis of Spatial Elements in the Time Series

According to the above preliminary analysis of the spatiotemporal characteristics of events around faults and the analysis process of the frame model, we calculated the detailed data statistics of a number of partitions from $2 \sim 50 \sim +\infty$, as shown in Table 3.

The size of microelements mainly depended on the number of microseismic events around the faults and the boundary size of the model. Table 3 shows that since there were 23 grids, the number of grids increased. The maximum number of events in each micro-unit fluctuated evenly between two and three. In light of this, if we subdivided the number of meshes, on the one hand, it would increase the computational complexity and difficulty of the numerical simulations; on the other hand, it would have no practical physical significance.

The Average Fraction of Each		Micro-Unit Size		Maximum Number of	
Side of the Total Cuboid	Length (m)	Width (m)	Height (m)	Events All Micro-Un	
2	150.00	100.00	125.00	52	
3	100.00	66.67	83.33	14	
4	75.00	50.00	62.50	26	
5	60.00	40.00	50.00	13	
6	50.00	33.33	41.67	12	
7	42.86	28.57	35.71	13	
8	37.50	25.00	31.25	8	
9	33.33	22.22	27.78	10	
10	30.00	20.00	25.00	7	
11	27.27	18.18	22.73	8	
12	25.00	16.67	20.83	8	
13	23.08	15.38	19.23	6	
14	20.00	14.29	17.25	6	
15	21.45	13.22	16.67	6	
15	20.00	13.55	15.62	5	
10	10.75	12.30	13.03	3	
1/	17.65	11.70	14./1	4	
18	16.67	11.11	13.89	5	
19	15.79	10.53	13.16	4	
20	15.00	10.00	12.50	5	
21	14.29	9.52	11.90	5	
22	13.64	9.09	11.36	4	
23	13.04	8.70	10.87	4	
24	12.50	8.33	10.42	3	
25	12.00	8.00	10.00	3	
26	11.54	7.69	9.62	2	
27	11.11	7.41	9.26	2	
28	10.71	7.14	8.93	3	
29	10.34	6.90	8.62	3	
30	10.00	6.67	8.33	2	
31	9.68	6.45	8.06	3	
32	9.38	6.25	7.81	3	
33	9.09	6.06	7.58	3	
34	8.82	5.88	7.35	3	
35	8.57	5.71	7.14	3	
36	8.33	5.56	6.94	2	
37	8 11	5 41	6.76	- 2	
38	7.89	5.26	6.58	- 3	
39	7.69	5.13	6.41	2	
40	7.50	5.00	6.25	2	
40	7.30	1.88	6.10	2	
42	7.52	4.00	5.05	2	
42	7.14	4.70	5.95 E 91	2	
	6.82	4.00	5.01	2	
44	6.67	4.00	0.00 E E 4	2	
43	0.0/	4.44	0.00 E 40	2	
40	6.52	4.35	5.43	2	
47	6.38	4.26	5.32	3	
48	6.25	4.17	5.21	2	
49	6.12	4.08	5.10	2	
50	6.00	4.00	5.00	2	
:	:	:	:	:	
	•	•	•	•	

Table 3. The space node division table.

Note: (1) The overall sample size was 300 m \times 200 m \times 250 m; (2) the micro-units were defined according to their similarity to the overall sample.

In addition, it can be seen in Figure 9 that the mesh number was closely related to the fitting degree for solving the fractal dimensions under different division conditions. The main performance was as follows: the more partitions, the better the fitting degree for the fractal dimension solution, which tended to be stable and converged gradually. We used a mathematical asymptotic horizontal line to represent R², which was the determining coefficient of the partition number and fitting degree. The interlevel points of these two progressive horizontal lines and the actual solution curve could fully verify the division number, as shown in Figure 9. The black vertical line was accurate, i.e., 23 was the best number.



Figure 9. A comparison of the fitting coefficients of the maximum events and fractal dimension values in microcells using different grids.

According to this method, the optimal number of cells for the overall microcell division was 23 and the minimum cell size was about 13.04 m in length, 8.70 m in width, and 10.87 m in height. As the statistical framework of the model was related to the scope of the analysis and research, the maximum grid size was 150 m \times 100 m \times 125 m.

4.3. Analysis of Spatiotemporal Fractal Dimension Laws

4.3.1. Fractal Dimension Distributions

Using the microseismic monitoring system and our fractal statistical framework model, different fractal dimension values were set, and marked and damaged areas were accurately identified and analyzed. In this study, it was assumed that each micro-unit was formed of a group of micro-geometric points, the coordinates of which could be determined, and the distribution proportions of different fractal value intervals could be regarded as carriers. According to the four-time stages, we statistically analyzed the number of events in each micro-unit and calculated their corresponding fractal dimension values. The specific division number was 23 and the division form was a cuboid of 13.04 m \times 8.70 m \times 10.87 m. All 52 microseismic events that occurred in the different stages were statistically analyzed and the fractal dimension values were obtained by fitting the line of Formula (1), as shown in Figure 10.



Figure 10. The fractal dimension distributions.

4.3.2. Numerical Simulation Analysis of Fractal Dimension Distributions Global Analysis of Fractal Dimension Features

Using MATLAB simulations and interpolation analysis, the distribution of fractal dimension values in each micro-unit was plotted in the simulation model, as shown in Figure 11. The virtual grid coordinate points were used to analyze the distributions of fractal dimension values and could reflect the accumulation, extension, and directivity of near-fault microseismic events on the plane. The nucleation trend of the fractal dimension values in the three-dimensional space could be calculated by synthesizing views in all directions. This showed the trend of weakening, dispersion, and disappearance, which reflected the obvious spatial fractal distribution characteristics. This distribution showed that the rock mass near the fault first experienced a shear break-weakening breach, was then dominated by a tension moment, and finally formed a closed fracture surface. This was closely related to mining disturbances, progress, and distance. With the increase in the fractal dimension D, more damage and larger events became consistent with the near-fault development characteristics.

Specifically, the data characteristics of the overall spatial fractal dimension value distribution are shown in Table 4.

D Value Range	Stage 1	Stage 2	Stage 3	Stage 4
[2, 3)	0	0	0	0.29%
[1, 2)	16.00%	0.75%	0.36%	0.29%
[0.91, 1)	1.33%	0	0	0
[0.78, 0.91)	0	0.75%	1.07%	0.87%
[0.65, 0.78)	32.00%	0	0.71%	1.73%
[0.52, 0.65)	0	0.75%	2.50%	1.16%
[0.39, 0.52)	0	2.99%	2.86%	2.31%
[0.26, 0.39)	0	5.22%	4.64%	4.91%
[0.13, 0.26)	14.67%	5.22%	6.43%	4.05%
$(-\infty, 0.13)$	36.00%	84.33%	81.43%	84.39%

Table 4. The interval distribution ratios of the overall fractal dimension values in each time stage.



Figure 11. A perspective cloud chart of the fractal dimension interpolation under different perspectives in each time stage.

From our preliminary data statistics, we found that interval divisions that were multiples of 0.13 had obvious data segmentation rules (Figure 12). ① From the first stage to the fourth stage, the proportion of fractal dimension values D between 0 and 0.13 was relatively large (accounting for 84.39%), especially when destruction reached the fourth stage. ② From the first stage to the fourth stage, the range of fractal dimension values was approximately 0 and their proportions decreased, which also reflected the gradual enhancement of the accumulation of microseismic events near the faults; for example, from the first five levels to the final level. ③ In each stage, the proportion of larger fractal dimension values gradually decreased, indicating that most of the initial stage comprised the accumulation of small events, later forming an accumulation of large events until damage occurred.



Figure 12. A schematic diagram of the fractal dimension value distributions in overall space in the different time stages.

Middle-Level Analysis of Fractal Dimension Features

After the MATLAB simulations and interpolation analysis, the fractal dimension value interpolation distribution of each middle segment was plotted in the simulation model for the different time stages, as shown in Figure 13.



Figure 13. A contour map of the middle-level fractal dimension interpolation in the different time stages.

The fractal dimension value shown in Figure 11 was from the initial stage, which had small values and weak changes. The first stage did not conduct interpolation analysis; however, the specific characteristics of the second, third, and fourth stages are fully demonstrated. Specifically, it could be seen from the parallel analysis of each independent middle segment in the time series that the events became more dispersed, especially in the fourth stage. In terms of spatial elevation, in the initial stage, it was low in the southeast and high in the northwest. The formation of inclined surface features was consistent with the fracture cracks and bedding structures found in the field. By analyzing the distribution characteristics of each middle segment of the fractal dimension values, the accumulation, extension, and directivity of near-fault microseismic events could be evaluated. From the dynamic comparisons of the same coordinate areas, we found that the fractal dimension values constituted the trend of coalescence and nucleation at different elevations.

Based on the simulation analysis of the fractal dimension interpolation in each middle segment, Table 5 presents the results at the statistical level of the fractal dimension proportion data.

D Valua Panga	+300 m Middle Level			+350 m Middle Level			+400 m Middle Level		
D value Kalige	Stage 2	Stage 3	Stage 4	Stage 2	Stage 3	Stage 4	Stage 2	Stage 3	Stage 4
[2, 3)	21.55%	8.88%	10.02%	13.23%	7.94%	10.02%	19.09%	2.27%	1.89%
[1, 2)	17.77%	32.70%	35.54%	32.33%	27.79%	35.73%	34.03%	5.48%	19.66%
[0.91, 1)	35.54%	13.99%	18.34%	15.88%	17.01%	15.88%	4.73%	6.62%	14.74%
[0.78, 0.91)	2.84%	11.91%	10.40%	4.54%	18.15%	13.04%	5.10%	9.26%	15.12%
[0.65, 0.78)	2.65%	11.53%	6.62%	3.40%	12.48%	8.32%	4.35%	7.94%	11.15%
[0.52, 0.65)	1.89%	9.07%	6.24%	4.16%	5.10%	5.10%	6.05%	7.18%	7.94%
[0.39, 0.52]	1.89%	3.97%	4.73%	2.46%	3.59%	3.21%	3.59%	7.94%	6.24%
[0.26, 0.39)	1.70%	3.40%	3.21%	2.84%	3.59%	2.46%	4.54%	7.18%	5.29%
[0.13, 0.26)	2.27%	1.89%	1.89%	2.27%	2.46%	1.89%	3.21%	8.51%	4.16%
$(-\infty, 0.13)$	8.32%	2.65%	3.02%	13.42%	1.89%	4.35%	13.04%	37.62%	13.42%

Table 5. The interval distribution ratios of the fractal dimension values of each middle level in each time stage.

The process of near-fault microseismic events gathering, nucleating, and ultimately weakening could be supplemented and demonstrated according to time stage and middle distribution level. A comparison of the main features is shown in Figure 14. The middle segments or periods with high proportions were highly consistent with the nucleation mode and direction, especially the distributions of the interpolation contours. The microseismic events were concentrated outside the upper and lower layers of the slip plane near the faults and showed the trend of stress concentration and release (i.e., the initiation and expansion of cracks near the faults), leading to a gradual increase in crack closure and the shear failure of the rock mass.



Figure 14. A distribution diagram of the fractal dimension values in the middle levels of the different time stages.

4.4. Analysis of the Relationships Between Fractal Dimensions and Rock Mass Failures

The above sections have presented a targeted comparison and analysis of the spatiotemporal elements of near-fault microseismic events, including photos of the actual working conditions of local rock mass fractures. Next, we analyzed the change laws of fractal dimension data in combination with the characteristics of the actual middle level of the mine and the microseismic events.

4.4.1. Fractal Dimension Values and the Number of Events Under Different Spatiotemporal Conditions

The distribution changes in the D value of the microseismic events near the faults and the number of events in each middle segment were evaluated in each of the different time stages (as shown in Figure 15) to study the correlations between them and the actual working conditions.



Figure 15. A comparison chart of the fractal dimension values and the number of events in the middle level of each time stage. (a) Changes in fractal dimension at different stages; (b) Changes in the number of events at different stages.

In the above analysis, three key middle segments with obvious and strong concentrations of microseismic events had the most involvement; these were centralized and targeted. The distribution of microseismic events generated near the faults and the surrounding damage extended from top to bottom, mainly covering +450 m to +200 m and totaling 250 m.

In the multistage simultaneous mining processes at Ashele Copper Mine, 50 m is taken as the middle level of each division. According to the specific mining conditions in the different middle levels combined with the near-fault characteristics and surrounding activity, the microseismic events in each middle level were counted in each different time stage. On this basis, a parallel comparative analysis of the fractal dimensions was carried out.

It could be seen that in the relationships between fractal dimension values and spatiotemporal elements, the deeper the burial depth, the more serious the damage, as shown in Figure 15a. The larger the stress, the larger the mining disturbance. In the fourth stage, the D value changed 1.2~1.67~1~1.33~1 from the middle level of +200 m to the middle level of +450 m. The main event was in the middle of +400 m, which was analyzed based on three aspects: nucleation and accumulation, the process from disorder to order, and dimension reduction, all of which corresponded to the development process of actual potential faults. In the first stage, there was little difference between the middle levels. With the aggravation of the damage degree of the potential small faults, the fractal dimension values in the third and fourth stages differed significantly between the middle levels. The same trend existed from the middle level of +300 m or +350 m to the middle level of the shallower or deeper parts, which first increased and then decreased.

It could also be seen that in terms of the relationships between the number of microseismic events and spatiotemporal elements, the distribution was consistent with the fractal dimension value, as shown in Figure 15b. The number of events in the middle level of +400 m was the largest. The number of events changed from the middle level of +200 m to the middle level of +450 m by 5~6~5~4~11~1. From the first stage to the fourth stage, the number of events increased in each middle stage. The same trend existed from the middle level of +350 m to the middle level of the shallower or deeper parts, and the number of microseismic events first increased and then decreased.

Generally, it can be seen from Figure 15 that the number of events and the fractal dimension values of each middle level involved in near-fault development had obvious corresponding characteristics in terms of spatiotemporal elements. Furthermore, compared to the actual working conditions, the fractal dimension values and their characteristics truly reflected the characteristics of near-fault rock mass failures in more detail, i.e., the spatiotemporal fractal dimension values were closely related to activity intensity, which could provide ideological and technical support for creating safe environments in underground mines.

4.4.2. Comparisons and Analysis of Other Parameters of Working Conditions

As mentioned above, it could be seen that the various characteristics of the fractal dimension values of the potential small faults in each middle segment further demonstrated the changing relationships between the fractal dimension values of spatiotemporal elements and the actual damage from potential small faults.

We analyzed the overall correlation of the radiation energy, Richter magnitude, seismic moment, and source radius of the microseismic events near the faults in the different time stages, as shown in Figure 16. This figure shows that with the advance of the mining processes in the time series, the stress near the potential faults was concentrated, the number of microseismic events around the faults increased sharply, and the activity increased. The rock mass failures had obvious correlations between the four stages. This was mainly reflected in the radiation energy (Figure 16a), Richter (Figure 16b), seismic moment (Figure 16c), and source radius (Figure 16d) of the microseismic events throughout the time series.

This consistency with time showed that the rock mass failures had obvious correlations between the four stages. In particular, on the one hand, the radiation energy of the microseismic events was consistent with the seismic moment and the energy and seismic moment suddenly decreased after a concentrated rise. On the other hand, the Richter magnitude response was generally consistent with the source radius response, although the latter was more sensitive.



Figure 16. A comparison diagram of the changes in the main parameter of the microseismic events. (a) radiant energy; (b) richter magnitude; (c) seismic moment; (d) source radius.

5. Discussion and Conclusions

5.1. Discussion

This article focuses on practical applications and engineering practices. In order to analyze, study, and verify the physical relationship and intrinsic connection between fractal theory and its fractal dimension with microseismic monitoring data, we conducted smallscale industrial experiments on the mining site. This engineering case aims to characterize the process of fault occurrence during ore body mining through fractal interpretation of microseismic data, laying the foundation for predicting fault damage in actual mining engineering.

We performed the experimental verification and determination of practical application in the context of actual engineering. In our preliminary research process, analysis and discussion were conducted on acoustic emission experiments in the laboratory, rock samples, and small-scale. This study preliminarily validated the feasibility of using acoustic emission data to characterize rock failure, as described in references [21]. And with the increase in acoustic emission data, the rock failure process and data aggregation show a process from chaos and disorder to order. This is the theoretical connection and experimental basis studied in this article.

Regarding the importance of on-site method validation in engineering, at the technical and management levels of mining sites, the key is to be able to solve practical problems on site. After years of on-site work in mines, our team has found that there is still a growing gap between theoretical analysis and experimental verification in solving practical problems on engineering sites. Therefore, based on the combination of fractal theory and acoustic emission experiments, this article delves into the frontline of mining sites to verify the effectiveness of this method.

When it came to determining the fundamentals of physical models, the relevant physical foundations were thoroughly analyzed in the literature [21]. This article mainly took the Ashele copper mine as a typical deep hard rock mine case and constructed a

microseismic monitoring system. Using the constructed framework model and fractal calculation method, the temporal spatial fractal dimension distribution characteristics of microseismic monitoring data in three main sections of the Ashele copper mine were studied. The combination of 3D reconstruction technology of monitoring data and fractal theory effectively characterized the failure process of rock mass. The spatiotemporal distribution and clustering degree of seismic sources represented by fractal dimension reflected the evolution trend of faults. The effectiveness of acoustic emission data reconstruction and fractal theory in characterizing rock mass structural failure was demonstrated.

Overall, this method can compensate for the shortcomings of traditional analysis methods and provide new ideas related to the study of rock mass structure. It also improved the spatiotemporal comprehensive fractal dimension analysis strategy for rock mass fracture sources in mining areas. With the development of computer technology and the widespread application of microseismic monitoring technology, three-dimensional reconstruction and fractal dimension will play an important role in the analysis, characterization, and prediction of rock engineering failure. The fractal analysis of spatiotemporal seismic parameters in mining earthquake sources provides reliable indicators for dynamic hazards. In addition, based on the specific application and practice of fractal theory in the mining field, we suggest that in future research in other fields, fractal models can be applied to other mining areas and scene analysis, and even machine learning techniques can be integrated to improve our ability to predict destructive behavior.

5.2. Conclusions

We studied the fractal characteristics of spatiotemporal elements of microseismic events near faults and surrounding areas during the deep mining process of typical mines. The conclusions are as follows:

- (1) A fractal theory-based method for analyzing microseismic spatiotemporal elements has been proposed. Through the three-dimensional reconstruction model of the spatiotemporal elements of microseismic monitoring data in mines, the optimal number of cell divisions was determined to be 23, with a minimum cell size of approximately 13.04 m in length, 8.70 m in width, and 10.87 m in height. This can provide a three-dimensional microscopic representation of potential nearby faults within the research scope, which is helpful for understanding the specific tectonic incubation process. The fractal dimension of fractal theory was used to construct a three-dimensional characterization model of rock mass failure and finely analyze the characteristics of rock mass failure.
- (2) A set of microseismic events recorded near and around the fault were evaluated for a comprehensive analysis of the fractal law of the spatiotemporal distribution of seismic sources near the fault. According to the temporal variation characteristics of microseismic activity, it is divided into four stages. It is necessary to analyze the relationship between spatial fractal dimension values within the model and mining seismic activity. In all four stages, the main fractal dimension D value shows a variation pattern from 1.2~1.67~1~1~1.33~1 from the +200 m to +450 m range. There is a trend of increasing first and then decreasing from the middle of the analysis model, either upwards or downwards. Overall, the number of events and fractal dimension values involved in the development of near-fault zones have strong consistency in terms of their spatiotemporal elements.
- (3) A change in the fractal dimension can reflect the degree of clustering and nucleation characteristics of mining earthquake sources. Specifically, from the perspective of the spatiotemporal fractal dimension distribution of microseismic monitoring events, the fractal dimension value of microseismic events is closely related to the distribution

24 of 26

around faults, mainly presenting an ellipsoidal spatial distribution, which has a good correspondence with mining intensity, direction, and periodicity. In particular, in the third and fourth stages, there is strong consistency in the agglomeration nucleation trend and the distribution level of each middle segment.

(4) Our findings were verified by other parameters of the mining earthquake source and the spatiotemporal fractal dimension of the potential small fault incubation process. The main event occurred in the +400 m section, which was analyzed based on three aspects: nucleation and aggregation, the process from disorder to order, and the dimensionality reduction process, all of which correspond to the actual development process of potential faults. The relationship between the number of microseismic events and spatiotemporal elements is consistent with the distribution of fractal dimension values. The number of events varies from 5~6~5~4~11~1 from the +200 m section to the +450 m section. As the mining process progresses in the time series, the radiation energy, Richter magnitude, seismic moment, and focal radius of microseismic events show a clear correlation within the four stages, with the main body showing an increasing trend followed by a decreasing trend.

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