Study on coal-rock interface characteristics change law and recognition based on active thermal excitation

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\textbf{ABSTRACT}

For recognizing the coal-rock interface efficiently, the infrared thermal images of coal-rock interface excited by active thermal excitation are tested and extracted which results in rise of coal and rock with different spatiotemporal characteristics and the infrared temperature attenuation law of coal and rock surface are analysed. The coal-rock infrared image is segmented and denoised to recognize the coal-rock interface with different ratio. The experimental results show that: (1) Under the active thermal excitation, the infrared temperatures of coal, rock and transition layer increase at different rates with a faster temperature growth of coal and the growth of rock temperature is relatively gentle. With the increase of excitation distance, the temperature decreases gradually and fluctuation of surface temperature occurs due to closer distance; (2) No matter the coal seam or the rock stratum, the temperature decreases linearly during the cooling process; (3) The results of image recognition technology based on local optimization and adaptive radius constrained principal curve algorithm are consistent with the actual test samples of coal rock ratio and the maximum error is 0.56%. The analysis results in coal-rock interface recognition for improving the cutting efficiency of shearer and realizing intelligent drum height adjustment control.

\textbf{Introduction}

In recent years, with the rapid development of industrial automation technology, advanced automatic control technology has also been successfully applied in coal mine working face, the coal mining method is also gradually developing to automatic mining (Jiping & Bang, 2017; Zhongchao & Yongjun, 2018). This testing facility has been developed to present the foundations of automatic switching technique, which is a broad phrase that covers the management and operation of activities involving continual explicit human interaction. Its structure is highly basic and flexible, enabling the ultimate customer to either understand and generate information clearly. Coal-rock interface recognition is one of the key technology to reduce the working staff and realize unmanmed mining face, more and more experts and scholars are committed to the research of coal-rock recognition technology(Jing & Bin, 2017; Yiming et al., 2017). Yunxia and Xianglong (2018); Yunxia and Yimin (2016) propose a coal-rock recognition method to characterize coal and rock images effectively which is named local constraints self learning (LCSL). This method has strong discrimination and robustness, and achieves a good recognition effect. Compared with the original coal-rock recognition method, the average recognition rate has increased by 1% to 3%. Qiang et al. (2017) and Qiang and Zhiheng (2018) establish the dynamic identification model of coal-rock interface of Shearer based on the minimum fuzzy degree optimization by means of testing and extracting the infrared thermal images of pick cutting under different coal-rock ratio, analyzing the distribution law of surface temperature field and the characteristics of cutting flash temperature, and setting up the cutting temperature characteristic database under different coal-rock ratio conditions. Because fuzzy optimization is a well-known optimal control issue in machine learning, production, and administration, developing generic and workable fuzzy optimization techniques is critical in both practical and theoretical. Jie and Di (2016) formed a complete shearer vibration information database by collecting and analyzing the actual vibration information under different cutting conditions. At the same time, through the time-domain analysis of vibration data, the difference of vibration characteristics between coal cutting and rock cutting conditions is summarized, and an effective coal-rock identification method is proposed. Liu et al. (2019) take distinctive visual features of coal and rock into consideration, the multi-scale feature fusion coal-rock recognition (MFFCRRR) model based on a multi-scale Completed Local Binary Pattern (CLBP) and a Convolution Neural Network (CNN) is proposed in this paper. The CLBP classifier is a finished description.

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of the local binary pattern (LBP) that seek to enhance the LBP for rotation-invariant features extraction. This operation suggests that every pixel be represented by a digital signal computed by 8 surrounding pixels. Experimental results show the coal-rock image recognition accuracy of the proposed MFFCRR model reaches 97.9167%, which increased by 2%–3% compared with state-of-the-art coal-rock recognition methods. Miao et al. (2018) first establish three layered model of coal-rock and give the mathematical analysis of this model. Then numerical simulation and field experiment are carried out. Finally, in order to interpret radar image, an improved image segmentation algorithm is proposed. The experimental results show that it is feasible to detect coal-rock interface by GPR and the improved algorithm is well to interpret radar image of coal-rock interface. the coal-rock recognition is realized by extreme learning machine (ELM) based on the extracted signal features. Ensemble learning devices are feed-forward neural systems by including a thin layer or various levels of hidden units for categorization, stagnation, grouping, sparsely populated estimation, compaction, and pattern recognition, in which the variables of hidden units (not only the strength training linking input data to hidden units) do not have to be synchronised. The experiment results show that the overall recognition accuracy is 91.7% under the actual cutting condition, which verifies the effectiveness of the proposed method in coal-rock recognition.

At present, the research status at home and abroad has not studied the coal and rock properties of active excitation (Guoxin et al., 2017; Qingjun et al., 2017; Wang et al., 2014). Due to the physical characteristics of coal and rock, the response to temperature excitation is quite different, and the endothermic effect of coal is far greater than that of rock (Dorota & Tamer, 2019; Yu & Mao, 2020). Therefore, the active thermal excitation method is used to analyze the temperature rise characteristics of coal and rock with different spatiotemporal characteristics and the infrared temperature attenuation law of coal-rock surface quantitatively. The local optimization and adaptive radius constrained principal curve algorithm is used for image recognition of coal-rock specimens with different proportions. The results of image recognition technology based on local optimization and adaptive radius constrained principal curve algorithm are consistent with the actual coal rock ratio of test samples, and the maximum error is 0.56%. This paper provides a new idea and method for coal-rock recognition, and theoretical basis for intelligent drum height adjustment.

**Infrared thermal imaging device for coal and rock by active thermal excitation**

**Preparation of coal-rock specimen**

The coal rock specimen is poured, and the boundary between coal and rock is random (Magdalena, 2019; Zhang et al., 2016). In this paper, coal, sand, cement and binder are used to pour coal and rock parts, respectively. The material ratio of coal-rock specimens in the pouring process is shown in Table 1. The function of binder is to accelerate the forming of coal-rock specimens. According to the experimental requirements, the size of coal-rock specimen is 450 mm × 350 mm × 100 mm, and the formed specimen is shown in Figure 1.

**The construction of the experimental system of coal rock image acquisition**

Due to their own physical characteristics, coal and rock show different characteristics in temperature rise and temperature drop under thermal excitation (Bechikh et al., 2015; Fatemeh Sadat & Hadi, 2020; Sciacca et al., 2020). The overall structure of the coal rock interface recognition experimental platform with active excitation is shown in Figure 2.

A thermal imaging camera (also referred as a TIC) is a form of infrared thermometer that is commonly utilised firefighters. Thermal sensors enable rescuers to observe regions of temperature despite fog, obscurity, or temperature obstacles via converting thermal light to illumination. By identifying and collecting varying degrees of infrared energy, temperature sensors can directly measure. This illumination is undetectable towards the unaided eye, however if the pressure is increased sufficient, it may be experienced as warmth. The experimental platform mainly includes image acquisition system, infrared thermal imager, thermal excitation device, light source support frame, photometer, slide table, coal rock specimen and bearing platform.

### Table 1. Ratio of coal and rock materials.

| Materials      | Coal | Sand | Cement | Binder |
|----------------|------|------|--------|--------|
| part of coal   | 85%  | 0%   | 10%    | 5%     |
| part of rock   | 0%   | 85%  | 12%    | 3%     |

*Figure 1. Formed coal-rock specimen.*
Image acquisition is the operation of acquiring a visual since a source, generally physical devices such as webcams, scanners, etc., in visual processing and artificial intelligence sight. It seems to be the most crucial stage in the workflow sequence since the software cannot do any analysis outside of a photograph. The fundamental role of luminaires is to create visual or near-visible incident radiation for lighting system and specialist purposes. Technologies comprise conventional, fluorescence, and high-intensity discharging (HID) lights, and also pin- or screw-based solid-state illumination (SSL).

The coal-rock specimen is placed on the bearing platform, which can slide on the sliding platform to adjust the distance between the specimen and the thermal excitation device. Thermal excitation is a mechanism in which structural oscillations give sufficient power to transport particles to an elevated energy range, including a greater intense sublevel or excited state, inside a photonic crystalline structure. Photon relaxing occurs whenever an electro-chemical reaction returns to a form of photons. The thermal excitation device and the infrared thermal imager are connected with the image acquisition system through the communication cable, which can realize the real-time image acquisition and control of the thermal excitation device. The infrared thermal imager used in this test system is a German VCi ET780 high thermal sensitivity detection expert infrared thermal imaging system. InfraTec’s active thermal imaging application IRBIS® 3 is a contemporary, widely useable thermal infrared mechanical testing instrument. Through introducing a temperature wave into the standardized test, dynamic temperature sensor enables for the non-destructive identification of surface defects including joint faults, swim bladders, fractures, or debonding. Active thermal excitation equipment is used together with infrared thermal imaging system, and high performance active thermal imaging application software for research and development of Irbis 3 active online is configured accordingly. The active thermal excitation device is connected with the infrared thermal imager through a communication cable to realize synchronous imaging. Thermal imaging is a technique for gathering information about things utilizing infrared rays and temperature difference, especially in low-light situations, in addition to creating photographs of objects. It’s a technological breakthrough that has a wide variety of applications across time. In order to monitor the light intensity of active thermal excitation equipment in real time, DT-1309 multi-function digital photometer was used to detect the light intensity on the specimen. In chemical, photometry is frequently utilised examine fluids and mixtures. It can be used to determine the weight of organo-metallic components in a fluid or mixture. It is used in astrophysics to estimate frequencies by using filtering to block some frequencies while permitting other frequencies to pass over.

**Characterization of thermal excitation temperature rise of coal and rock with different spatiotemporal characteristics**

**Infrared thermal image extraction for coal and rock**

The upper computer infrared thermal image data acquisition and analysis system can extract and replay the infrared thermal image information of coal-rock specimens in different periods. The system can also obtain the temperature characteristic information of different test points, and analyze the temperature–frequency curve of infrared thermal image under different pixel conditions. TDF graphs, which connect the severity of thermal occurrences of various time points with their periodicity, could be effective technique for assessing heat fluctuations. In Figure 3, a group of infrared thermal image samples of coal-rock specimens taken per 10 s under active thermal excitation are shown. It can be seen that with the increase of active thermal excitation time, the surface temperature of coal-rock specimen changes significantly, and the color difference is gradually significant, which can easily distinguish the boundary zone between coal and rock. The response of coal and rock to active thermal excitation varies with time and space. The quantity of detecting bits (receiver frequency) on the thermal camera determines the graphics performance. Every sensor measures the actual temperatures of the region of interest in which it is located. The far more sensor particles that are concentrated on the object, the more information that will see in the vision and more precise the assessment will be. Therefore, in order to obtain high-precision infrared thermal image of coal-rock interface to lay a foundation for realizing the recognition of coal-rock interface trajectory, the temperature variation of infrared thermography in different time and space need to be study.
Time effect analysis

Under the condition of the same coal-rock medium and active thermal excitation device position, the influence law of time variation on the temperature rise of coal and rock medium is studied. The distance between the active thermal excitation device and the coal-rock specimen is set as 2 m, and the test time is 120 s. The infrared thermal image of coal-rock interface is sampled every 5 seconds. Nine measuring points from P1 to P9 are set. Among them, P1 ~ P3 is coal seam, P4 ~ P6 is coal-rock boundary, namely transition layer, and P7 ~ P9 is rock stratum. Among them, P1 ~ P3 sampling points are coal seams, with the fastest temperature rise; P4 ~ P6 sampling points are coal-rock transition layer, the temperature is relatively lower than coal seam, but higher than that of P7 ~ P9. It
can be seen that under the action of active thermal excitation, the temperature of coal, rock and transition layer increases at different rates, among which the temperature of coal seam increases fastest, and the growth of rock temperature is relatively gentle.

**Space effect analysis**

In the process of coal-rock interface recognition under active thermal excitation, in addition to its own physical characteristics and time effect, another important factor is the vertical distance between coal-rock surface and active thermal excitation device. The differential between the stone and coal reflected radar waves obtained through radar on the disk layouts is used to determine the coal-rock functionality for classification. This approach has limitations in terms of environmental formations and anti-electromagnetic interfering capability. The closer the distance between the device and the coal-rock surface is, the smaller the radiation area is, the larger and more concentrated the radiation energy is; on the contrary, the farther the distance between the device and coal-rock surface is, the larger the radiation area is, and the radiation energy is relatively diffused.

In order to study the influence of space effect on the temperature rise of coal and rock specimens, four kinds of test experiments are carried out. The active thermal excitation distance is 2 m, 3 m, 4 m and 5 m, respectively. The test schematic diagram is shown in Figure 6.

In order to distinguish the temperature variation differences among coal seams, rock stratum and transition layer, three sampling points P1 (coal seam), P2 (transition layer) and P3 (rock stratum) are set, respectively, to conduct infrared thermal image test and acquisition experiment under different working conditions of active thermal excitation distance. The sampling points are shown in Figure 7. The sampling time is 100 s. In order to ensure the accuracy of the test results, it is necessary to wait for the coal surface to fully recover to room temperature after each test. The temperature–time curves of each sampling point with different thermal excitation distances are shown in Figures 8-10.

It can be seen from the temperature–time sampling curve of each sample in Figures 8-10, under the same excitation time, the characterization of coal seam, rock stratum and coal rock transition layer for different distance infrared thermal excitation is obviously different. With the increase of excitation distance, the temperature of the same excitation time gradually decreases. And the closer the excitation distance is, the more obvious the fluctuation of the surface temperature is, while the longer the excitation distance is, the more stable and regular the temperature rise is.

**Analysis of temperature attenuation law of coal and rock surface**

**Infrared image of infrared temperature drop of coal and rock**

The analysis of infrared image in the process of temperature drop after active thermal excitation is the key to analyze the infrared temperature attenuation rate of coal and rock surface, explore the optimal-cooling time and accurately identify the optimal-cooling temperature of coal-rock interface. Therefore, in the process of experiment, it is necessary to ensure the natural cooling of coal and rock samples after active thermal excitation. Thermal stimulation is a mechanism in which crystalline oscillations give sufficient force to transport electrons towards a higher frequency range, including a more powerful sublevel or excited state, inside a semiconductors crystalline structure. Photon relaxing occurs whenever an electron to a higher energy returns to a form of photons. During surface cooling of coal and rock samples, infrared thermal image information of different time is taken and extracted by infrared thermal
imager, and the temperature attenuation law of coal and rock after active thermal excitation is analyzed by infrared thermal image information. The modelling findings show that temperatures have a considerable impact on ultrasound frequency absorption. The ultrasonic frequency tends to reduce by 32.31% as the temperature exceeds from 20°C to 480°C. It's also discovered that when the temperature reaches, the size of the nearby acoustic wave grows. Figure 11 shows eight infrared thermal images of coal-rock specimens with surface temperature decreasing in 450 s after the active thermal excitation. It can be seen that the infrared temperature field of coal-rock specimens surface changes significantly with the increase of cooling time. In order to clearly analyze the temperature drop rates of coal-rock surfaces in different periods, six sampling points shown in the figure are set, respectively.

**Analysis on infrared temperature attenuation law of coal and rock**

The temperature curves of six sampling points P1 to P6 at different temperature drops are shown in Figure 12. It can be seen that the temperature of each sample shows a distinct downward trend with the increase of temperature drop time. The temperature curve oscillates slightly due to external disturbances during the cooling process, but the slope of each sample temperature curve is relatively close. A cooling system is an equipment that prevents the energy consumption of a building or equipment from surpassing the restrictions placed for technical and economical requirements. When oil in a mechanically gearbox overheats, it reduces its moisturizing ability, whereas the liquid in a hydro connection or conversion escapes due to the increased
temperature. It indicates that the temperature of either coal or rock decreases approximately linearly during cooling process after active thermal excitation. Therefore, for coal-rock specimens with the same physical properties, the cooling temperatures in different periods can be calculated by the initial cooling temperature and the cooling time. Divide every thermometer piece of information according to its

Figure 11. Infrared temperature images of coal-rock interface in cooling process.

Figure 12. Temperature curves of each sampling point.
associated time dataset to get an operating temperature, subsequently aggregate the whole of these responses to get a melting temperature. In other words, the mean temperature fluctuation is equivalent to the initial in degree proportional to the difference in duration.

In Figure 12, the highest temperature is the temperature curve of P2 sampling point, followed by P6, P3, P1, P4 sampling point, and the lowest temperature represents the temperature change of P5 sampling point. By sampling and fitting the temperature values at different time points of each sampling point, the temperature-time curves of each sampling point after fitting are shown in Figure 13.

Coal-rock interface recognition technology

Infrared image segmentation of coal and rock

The recognition process of coal rock interface based on infrared thermal image using fuzzy clustering segmentation algorithm is as follows:
(1) Initializing the coal (rock) cluster center \( v_i^{(0)} \);
(2) Calculating the distance from each pixel to the cluster center \( d_{ij}^{(1)} \);
(3) Calculating the fuzzy membership function \( u_{ij}^{(1)} \);
(4) Updating the cluster center according to the fuzzy membership function \( v_i^{(1)} \);
(5) Judging whether the membership function satisfies the stop condition. If it is satisfied, the iteration will be stopped; otherwise, return to step (2) to continue the iteration. The stop condition is shown in Formula 1.

\[
\max\left\{ u_{ij}^{(t)} - u_{ij}^{(t-1)} \right\} / \epsilon
\]  

The infrared thermal image of coal and rock surface is segmented by this algorithm, and the image before and after segmentation is obtained, as shown in Figure 14. As can be seen from the figure, the coal-rock boundary based on infrared thermal image is basically distinguished by using fuzzy clustering segmentation algorithm, but there are a lot of uneven segmentation surfaces on the edge of the segmentation result, so it is necessary to consider further optimization method to realize accurate extraction of coal-rock interface. Fuzzy C-means clustering, as such application of image processing technique, is an efficient and compact segmented approach. To maximize the grouping efficiency, the method incorporates the local products of surrounding pixels into the enhanced multi-objective physical equation.

Coal and Rock Trajectory Extraction Method Based on Principal Component Analysis

The fuzzy clustering segmentation algorithm is not ideal for the edge detection of coal-rock interface with rich details, so a principal curve fitting algorithm considering both edge smoothness and integrity is adopted. The algorithm extracts the edge point set of infrared image and looks for the smooth curve that passes through the “middle” of the edge point set and can reflect the overall shape of the edge points.

Take Figure 15 as an example, the principal curve is assumed to consist of vertex \( P_i = (i = 1, 2, \cdots, n) \) and segments \( L_{(i,j)} \) \( (j = 1, 2, \cdots, n - 1) \). \( P_S \) and \( P_e \) are fixed endpoint, \( n \) is the number of vertices, \( m \) is the number of data.

The Euclidean distance between each edge point \( d_t \) and the vertex \( P_i \) is as follows:

\[
D_{1t} = \sqrt{(X_{dt} - X_{Pi}) + (Y_{dt} - Y_{Pi})}
\]  

The Euclidean distance between each edge point \( d_t \) and the line segment \( L(i,j + 1) \) is as follows:

\[
D_{2t} = \frac{|P_tP_{j+1} \times P_jP_{i+1}|}{P_tP_{j+1}}
\]  

The smaller of the two is defined as the projection distance \( E_t \) from the data point to the curve.
Figure 14. The coal-rock image before and after segmentation.

\[ E_t = \min \{D1_{t,i}(i = 1, 2, \cdots, n), D2_{t,j}(j = 1, 2, \cdots, n)\} \]  \hspace{1cm} (4)

The data error is:

\[ E = \sum_{i=1}^{m} E_t \]  \hspace{1cm} (5)

By changing the number of vertices of the principal curve, the data error is minimized.

**Local optimization and adaptive radius constrained principal curve algorithm**

As shown in Figure 16, the starting point \( P_s \) and end point \( P_e \) of the data set are given. The circle is made with the starting point as the center of the circle and the distance \( R_1 \) and 0.9 \( R_1 \) between the starting point and the end point as the radius. The inner and outer circles are marked as \( R_{in}, R_{out} \) respectively. The mean value of the data points in the circle is inserted as the alternative vertex \( P_2 \), and the data error of the line segment composed of all data points and point \( P_1 \) and \( P_2 \) in the outer circle is calculated according to the formula. If the error is less than the preset upper bound of local error \( E_{max} \), the vertex \( P_2 \) is accepted. Then set point \( P_2 \) as the initial point and delete the data points inside the outer circle; Otherwise, reduce the radius and re select the candidate vertex until the vertex satisfying the condition is found.

**Evaluation and analysis of coal-rock interface recognition accuracy**

The local optimization and adaptive radius constrained principal curve algorithm is used to optimize the segmentation results of coal-rock interface infrared image, and the optimized segmentation results are shown in Figure 17. Figure 18 shows the comparison between the segmentation results of coal rock interface and the real coal rock interface. It can be seen that the segmentation result is highly close to the actual coal rock trajectory, indicating that the recognition result of coal rock interface is reliable.

In order to analyze the accuracy of coal-rock recognition results quantitatively and qualitatively, the coal seam residual quantity and rock erosion amount in 10 groups of experimental samples are used. The coal seam residual amount, rock erosion amount and total error percentage of each sample recognition results are shown in Table 2.

It can be seen from Table 2 that the recognition results have high recognition accuracy, and the coal seam residual amount and rock erosion amount are low. Among the 10 groups of sample recognition results, the maximum recognition error is only 56%, which shows that the recognition method has very high recognition accuracy, and has important guiding significance and practical value for realizing dynamic accurate recognition of coal-rock interface and automatic height adjustment control of shearer.
layer increases at different speeds, in which the temperature of coal layer increases fastest, the temperature of transition layer is second, and the temperature of rock layer increases relatively smoothly. With the increase of excitation distance, the temperature of the same thermal excitation time decreases gradually, and the closer the excitation distance is, the greater the fluctuation of surface temperature of coal-rock specimens is. When the excitation distance is far, the temperature rise is more stable and regular.

(2) The temperature of each sample shows a distinct downward trend with the increase of temperature drop time. The temperature curve oscillates slightly due to external disturbances during the cooling process, but the slope of each sample temperature curve is relatively close. It indicates that the temperature of either coal or rock decreases approximately linearly during cooling process after active thermal excitation. Therefore, for coal-rock specimens with the same physical properties, the cooling temperatures in different periods can be calculated by the initial cooling temperature and the cooling time.

(3) The image recognition results based on the local optimization and adaptive radius constrained principal curve algorithm are consistent with the actual coal-rock ratio of the specimens. The maximum error is only 0.56%, which showing that this method can recognize the ratio of coal-rock specimen accurately.

**Disclosure statement**

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**Authors’ contributions**

Qiang Zhang: Methodology, Project Administration, Manuscript editing; Junming Liu: Software, Validation; Jiaying Gu: Visualization, Manuscript Review and editing; Ying Tian: Design Framework, Resources, Validation.

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