

Automatic Annotation Method of Gangue Data Based on Digital Image Processing

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Abstract: An automatic annotation method of coal gangue image data based on X-ray acquisition is proposed. Firstly, the manually screened coal and gangue are sent to the X-ray acquisition device for image sampling. Secondly, according to the characteristics of the pure background of coal and gangue images, a gray threshold is used to detect. Further, the mask is used to purify the detected foreground objects, which obtain a single object image. At the same time, the manually screened coal/gangue is sampled and the category information of the currently detected objects is obtained at the same time, and the monomer sample database is established. Finally, based on the monomer sample library established, the monomers randomly were selected in the sample library and combined to generate sample images with classification and location. That is, the automatic annotation of coal gangue data is completed. The results show that the automatic annotation method of coal gangue image data through digital image processing can effectively annotate the collected coal gangue image data, with a high sample generation rate and annotation accuracy of 99%.

Keywords: coal; data annotations; gangue; image processing; X-ray

1 INTRODUCTION

In recent years, China is a large coal consumer, and in the process of coal mining, coal gangue sorting can greatly improve the quality of coal on the one hand, which reduces the impact of gangue on land occupation and environmental pollution on the other hand. At present, the methods of gangue sorting mainly include manual sorting, traditional mechanical sorting [1] and machine learning intelligent sorting methods based on digital images. The sorting method based on digital image is popular for being environmentally friendly, with high accuracy and speed of recognition and sorting.

In the sorting method of digital images, the object detection method based on Convolution Neural Network (CNN) [2, 3] can not only detect the classification of objects in the image, but also detect the position of the corresponding object [4-9], for the subsequent gangue sorting operation is of great significance. However, object detection networks generally require many already labeled training images for the neural network to learn [10, 11]. In practical applications, high-quality gangue images have high requirements for the light and other conditions of the coal mining site.

In order to achieve high-speed coal gangue sorting as the motivation, the number of raw coal products on the conveyor belt is generally more, so one image of the collected images may contain a lot of coal and gangue, and manual data annotation. Hence, the workload is extremely large. According to the image for visual classification, annotation accuracy is difficult to guarantee. An efficient, accurate and automatic gangue data annotation method is of great significance. The contribution of this paper is as follows. Based on the characteristics of the clean background of the coal gangue image, this paper adopts the gray threshold and other image processing methods to detect the foreground object, and the mask method is further used to purify the detected foreground object to obtain a single object image. This paper can effectively label the collected coal gangue image data, establish a more comprehensive section database, and have a more accurate theoretical model.

Ren et al. [4] applied the multi-scale method of wavelet transform and the rough set theory to extract the contour of coal gangue image respectively, so as to suppress noise and accurately extract edge features. Chen

et al. [7] pointed out that binarization of threshold determined by gray histogram could not solve the segmentation problem of coal gangue image in a real sense, and proposed an image segmentation algorithm: image distance transformation was carried out after image binarization processing, and then coal gangue image was submerged by gradient descent algorithm, so as to effectively detect image edge and segment coal and gangue. Liu et al. [8] used particle swarm optimization algorithm and Gaussian mixture model to extract image background in order to separate the object from the background, aiming at problems such as the blackened color of gangue and the obscure edge gradient caused by coal dust and moisture. In terms of image feature extraction of coal gangue, Cai et al. [29] are aiming at the problem of lack of representativeness and practicability of samples, selected six blocks of coal or gangue with different materials, texture characteristics and cleanliness, and analyzed the gray distribution law of images according to certain group methods under three kinds of light intensity respectively, so as to realize automatic recognition of coal gangue. However, if the selected coal gangue identification feature is a single parameter, there will be problems such as parameter coincidence and low recognition accuracy when extracting image features. Therefore, Hu et al. [12] selected gray histogram, fractal dimension and wavelet transform energy as recognition features, and established a 4-layer BP neural network model to achieve multi-feature fusion. Zhao et al. [13] extracted the grain features of coal gangue with gray co-occurrence matrix, and realized the recognition of coal gangue with support vector machine. Guo et al. [14] used the difference box dimension method to obtain the fractal dimension of coal gangue according to the extracted gray scale and texture characteristics, and proved that the fractal dimension of coal was greater than that of gangue through experiments, which provided a new idea for the research on the recognition of coal gangue. Chen et al. [15] studied the change rule of image features of coal gangue under different illuminance by extracting gray scale and texture features of coal gangue. It can be seen that the current research on coal gangue image recognition methods mainly focuses on two aspects: how to effectively segment the target and background in the image; how to accurately identify the image features of coal and gangue. Some researchers proposed that image brightness adjustment, median filtering and other preprocessing should be carried

out before image segmentation and feature extraction, so as to increase the difference between image target and background in color, brightness and texture, so as to facilitate image segmentation and feature extraction. However, most of this kind of research is in the theoretical and experimental stage, the image background and the target are very different, and the number of image samples is small, so it is not practical and universal. In addition, this kind of research requires artificial image preprocessing and feature selection, and there are some problems such as incomplete understanding of image target features and low accuracy of image recognition. Deep learning is a good solution to this problem. Through multi-layer nonlinear transformation, this technology learns hierarchical feature representation from big data in supervised or unsupervised ways and describes images from bottom to top level [16], avoiding the complex feature extraction process in traditional recognition methods.

In recent years, deep learning technology has been widely used in license plate recognition, face recognition, object detection and other aspects, and is currently a research hotspot in the field of computer vision. Its research in the field of coal gangue identification is also gradually developed. Based on deep learning technology, Jiang et al. [15] improved the classical convolutional neural network LeNet-5 from the aspects of input size, activation function, network depth, etc. After training, a network model capable of identifying coal gangue images was obtained, realizing the recognition and classification of coal gangue images. Wang et al. [16] proposed an image target detection and region shearing algorithm, and used deep learning technology to build a convolutional neural network model based on AlexNet, which solved problems such as training difficulties and overfitting caused by fewer data sets, and improved the accuracy of coal gangue recognition. In summary, it can be seen that the identification characteristics selected by each identification method are different. The key lies in how to obtain the characteristics that are easy to distinguish coal and gangue, so as to accurately and quickly identify coal gangue and provide a basis for subsequent separation and gangue discharge.

2 BASED ON THE THEORETICAL ANALYSIS OF COAL GANGUE IMAGE ANNOTATION

2.1 Automatic Data Annotation Method of Gangue

In the application of gangue sorting, there are many X-ray-based gangue sorting studies [12-17], and many methods can also produce good results, but the gangue sorting of this method is difficult to cope with the complex geological environment in China [18-25]. However, it is observed that the background of the image obtained by X-ray is pure, the outline of the coal gangue is clear, it is easier to obtain the foreground object through a specific algorithm, in special scenarios, the image to be labeled has a certain regularity, as long as the corresponding characteristics can be clarified, the automatic annotation scheme can be made in a targeted manner, although the method is not universal, but the effect can be guaranteed in specific application scenarios.

(1) Dual-energy X-ray imaging characteristics

According to the Lambert-Beer law, when X-rays penetrate a substance, they are closely related to the thickness and density of the substance. The thickness and

density are greater, the intensity of the rays received by the detector weaker, which is manifested in the X-ray image, that is, the coal or gangue is thicker, the pixel gray value is smaller. At the same thickness, the pixel gray value of gangue imaging is lower than that of coal. For coal and gangue alone, the basic situation of the change of pixel gray value is as follows. When coal and gangue enter the X-ray scanning area, the pixel gray value does not drop sharply, but slowly decreases to the minimum value. There are two reasons, one is that coal and gangue are generally spherical, thick in the middle and thin on both sides, so the edge area of the pixel gray value is smaller than the middle area. On the other hand, cesium iodide crystals in dual-energy X-ray detectors have a delayed effect when converting invisible X-rays into visible light, which in turn creates an afterglow effect.

However, regardless of the shape and thickness of coal and gangue that are X-ray scanned, the grayscale value of the imaging pixel produces a minimum value in the thickest area. Therefore, this paper introduces a target segmentation method for dual-energy X-ray images of gangue.

(2) Dual-energy X-ray image binarization method

Common image binarization methods include OTSU threshold segmentation, image segmentation method based on edge detection, and improved algorithms for both, such as OTSU tile threshold segmentation algorithm. When X-ray scanning imaging, if the target with thickness change is encountered, the gray value of the imaging pixel will be reduced, so a single-threshold segmentation algorithm based on the minimum gray value of the no-load image in the low energy region is proposed.

The specific method of image binarization can be described as follows. First, this paper obtains the low-energy region image H when X-ray scanning the belt under empty belt operation, and calculates the minimum pixel gray value h of the low-energy region image, that is, $h = \min(\min(H))$. Then, this minimum value is used as the segmentation threshold for the foreground and background of the high-energy image I' , which is $m \times n$ in size after filtering the median value of 3×3 . Finally, the pixels greater than this threshold h are set to 0, and the pixels less than or equal to this threshold h are set to 1. Then the segmented target is output Binarized image BW . Among them, 3×3 median filtering is used in this paper to remove fringed defects in X-ray images.

$$BW = \begin{cases} 0, I'(i, j) > h \\ 1, I'(i, j) \leq h \end{cases} \quad (1)$$

where: $i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

(3) Watershed algorithm

The watershed algorithm is widely used in the segmentation of adhesion targets in image segmentation algorithms. Its algorithmic idea can be described as: first, look for valley basins, that is, seed points (minimum points or areas). Then water is injected through the seed point until the water overflows to the watershed, the so-called watershed is the adhesion line at the adhesion image to be sought, the specific principle is shown in Fig. 3 to Fig. 6. The key point of the watershed algorithm application is to find the seed point, if the seed point calculation is too much,

it will produce over segmentation. If too little is calculated, under-splitting will occur. At present, there are two common seed point finding methods: distance transformation based on binarized image and limit corrosion. Among them, the method based on distance transformation calculates the minimum points, which is easy to over-segment the adhesion targets that are independent and contain neck features. The method based on extreme corrosion calculates the minimum point, which has a poor segmentation effect for multiple target adhesions of different sizes.

(4) Multiple grayscale threshold segmentation

Aiming at the target adhesion problem of X-ray images in the low-energy region of coal gangue, the specific algorithm flow is as follows. (1) The connected region of the binary image is detected and separated, and the separated binary image is multiplied by the original gray image to obtain the gray information image of the independent or adhesive target. (2) The gray information image is segmented by multiple gray threshold and connected region detection is performed. (3) The threshold with the largest number of connected domains in the process of multiple gray threshold segmentation is selected as the optimal threshold. The binary connected domain region segmented by this threshold is taken as the extreme region, namely the seed point, and then processed with the original gray image mask. (4) The image processed by the mask is segmented by watershed algorithm to obtain the binary image after watershed segmentation. (5) The binary image obtained from (4) segmentation is accumulated to obtain a non-adhesive binary image of the whole low-energy region high-energy image. The principle of multiple gray threshold segmentation is shown in Figs. 3 to 7, the ordinate represents the gray value, and the abscissa represents the pixel coordinate where:

$$h_1 = h - l \tag{2}$$

$$h_i - h_1 = (i - 1) \cdot l \tag{3}$$

Formula: take 10 for step 1, 10 for multiple gray domain value iterations.

During the iteration of multiple gray threshold segmentation, as the gray threshold decreases, the binary target area gradually becomes smaller or even disappears for independent targets. For adhesion targets, while the binarized target area gradually becomes smaller, multiple adhesion targets begin to separate, and smaller targets disappear when further segmentation occurs. Multi-gray threshold segmentation process visualization image.

2.2 Overall Design of Automatic Data Annotation Method for Gangue Sorting Based on X-ray

For the collected gangue image, as shown in Fig. 1, each sampling is for a single sample (coal or gangue), and then based on the image processing algorithm to separate the sample part in the sample data, obtain a sample map without background, use contour tracking, and do boundary rectangle fitting based on the boundary, crop the sample, and obtain a single image of each sample (mask treatment, only a clean image of the foreground object), at

the same time, because each sample is a single sample, therefore, the category of the single image is clear.

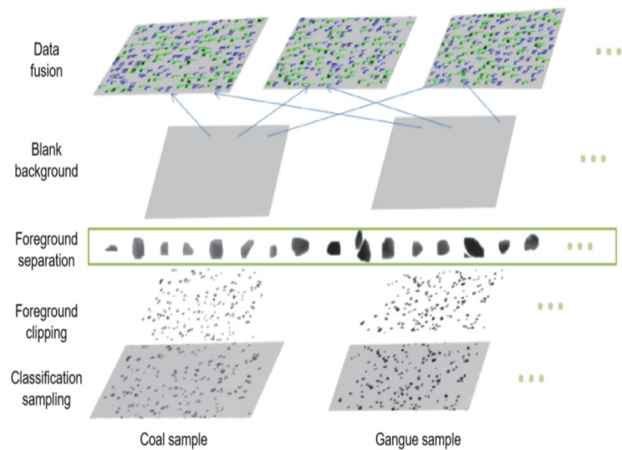


Figure 1 Schematic diagram of coal and gangue data processing

A database of monomer samples was established for all samples (including coal and gangue sampling, segmentation). Then, according to the extracted background, samples are randomly selected from the monomer sample database and subjected to certain random processing, and fused into the background according to a certain random position to generate a sample map containing both coal and gangue. Because each monomer sample category is known, when randomly fused into the sample, although a random algorithm is used, the position calculated by the algorithm can be saved and recorded, so the position and category of each coal and gangue in the generated data are clearly known, that is, the corresponding label of the data is complete. Fig. 2 shows the process diagram of the automatic data annotation method in this paper.

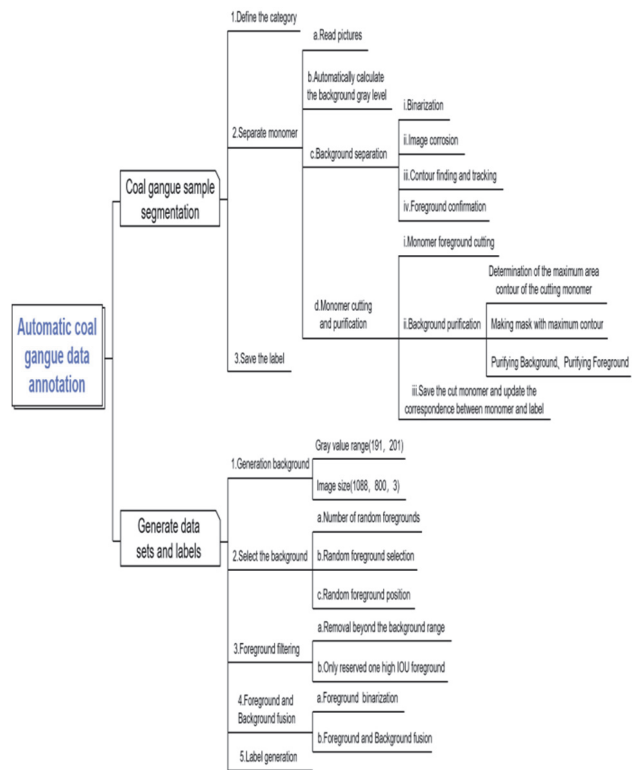


Figure 2 Flow diagram of automatic data annotation method for coal gangue sorting

3 TEST RESULTS AND ANALYSIS

3.1 Coal/Gangue Sample Monomer Segmentation, Establish Monomer (Coal/Gangue) Sample Bank

(1) Clear category: that is, based on raw coal for manual sorting, the raw coal is divided into coal sample set and gangue sample set and based on X-ray data collection, the typical gangue data diagram is shown in Fig. 3.

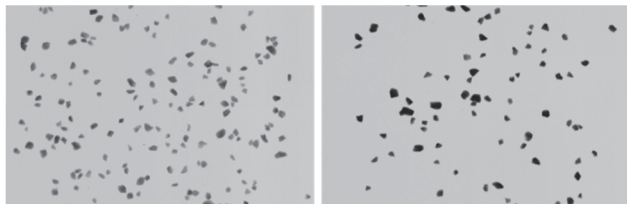


Figure 3 X-ray diagram of coal (left) and gangue (right)

(2) Separation of monomers:

A. The high and low coal and gangue image data collected in this paper (4 types in total) should be mapped and read;

B. According to the large gray difference between the background and coal/gangue objects, and the high proportion of background component pixels, automatically calculate the image gray mode as the background gray standard value;

C. Foreground separation: The standard value of the background gray level is subject to necessary relaxation (multiplied by the relaxation factor, 0.9 in this project, representing the range of the background gray level), and then the image is binarized (binary, determine a certain threshold, in the image, the pixel greater than the threshold is 1, and the pixel less than the threshold is 0), as shown in Fig. 4.

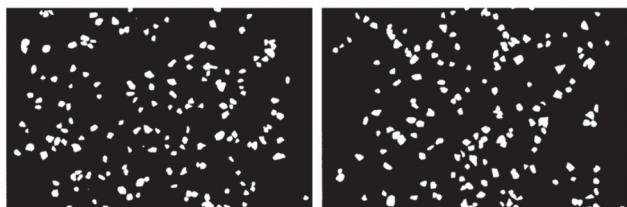


Figure 4 Binary transformation of coal (left) and gangue (right)

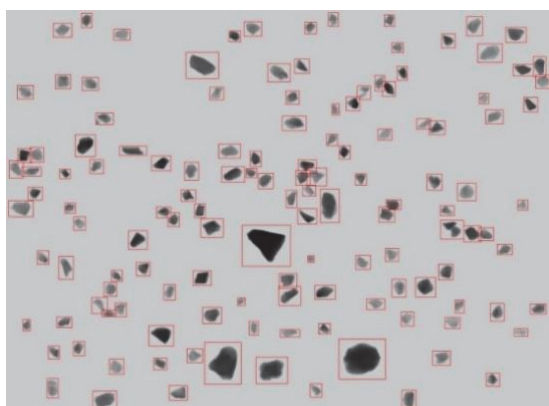


Figure 5 Separation of foreground objects (the red box marked as separation boundary)

After erode (a very mature morphological processing method) processing, the image of coal and gangue adhesion is broken, and then the open cv integrated contour algorithm (find contours) is further used to track the

foreground object. The tracked point set results are fitted with a rectangular frame (during the fitting process, due to the previous corrosion operation, the boundary of the foreground object will shrink. Therefore, this project will be appropriately relaxed), and further, the image noise points will be removed according to the number of pixels in the foreground object to obtain the real foreground object, as shown in Fig. 5. (That is, the area of the object is lower than the set threshold, which is considered as a noise point and does not have the characteristics of the foreground object).

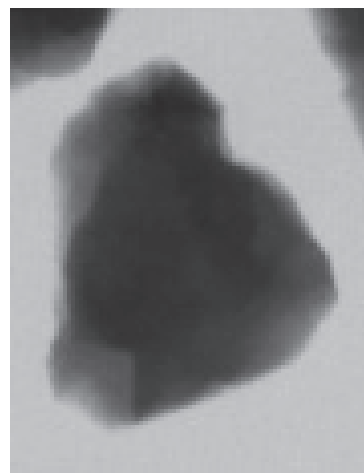


Figure 6 Cutting foreground image (the upper edge part contains images of other sample parts)

D. Monomer cutting and purification: As shown above, the coal/gangue foreground object in the X-ray image has a good search effect, and the monomer foreground image can be obtained by cutting according to the red marked box. However, some samples that are closer to each other will have images of other sample portions in the directly cropped monomer sample, as shown in Fig. 6.

In order to ensure the quality of the generated images, it is necessary to decontaminate the monomer sample images. In this article, the logic of designing the purification algorithm is as follows:

(1) Contour search for the cut single image, and filter out the largest area profile in the current sample diagram according to the area.

(2) Make a background purification mask (mask) with the largest contour as the center of the object, as shown in Fig. 7.



Figure 7 Purification mask

(2) On the basis of the generated purification mask, the pixel level bitwise addition operation is performed on the cut foreground. That is, the part with value in the mask (1, white part). The pixels at the corresponding positions in the foreground image are reserved, and all others are silent, as shown in Fig. 8. (The background in the left image is restored with gray values. In the actual sample library, the background is all blackened, as shown in the right image). The purified monomer image is saved and the monomer sample library is established. At the same time, the label corresponding to the single sample image of the sample library needs to be updated and saved after the entire sample library is established. In this paper, the number of experimental monomer samples is 26521.

(3)

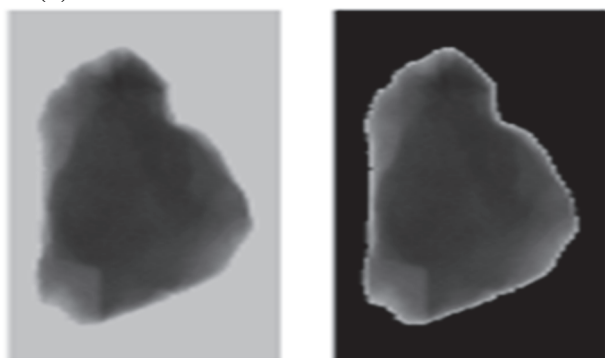


Figure 8 Background purification effect (left: restoration of background gray value)

3.2 Results and Discussion

1. Generate background: according to the calculation of gray value in the sample database establishment stage, it is clear in this paper that the gray range of the sample is (191, 201). At the same time, the size of the X-ray image used this time is clear, which is (1088, 800, 3). Based on this, a background image with a random gray value in the range of (191, 201) and a size of (1088, 800, 3) is generated.

2. Select the foreground: this article selects the monomer from the monomer sample library generated in the previous section to generate the model data set, including three random processes:

a. (1088, 800, 3) The number of monomers in the background map distribution is random, and the random range of the number is set to (50, 180).

b. Random selection of foreground monomers, that is, random selection of a certain number of monomers in the monomer repertoire, non-sequential or other regular selection.

c. The selected single image is randomly positioned in the background, further mimicking the distribution of the single body in the real scene.

3. Foreground filtering: Randomly distributed foreground mainly filters the following two types.

(1) Foreground beyond the background size range is filtered.

(2) The foreground of each random distribution is IOU calculated according to the position and the following foreground, and the subsequent foreground image above the threshold is deleted.

Where IOU represents the intersection over Union, represented by the intersection of two image frames divided by the union, as shown in Fig. 9.

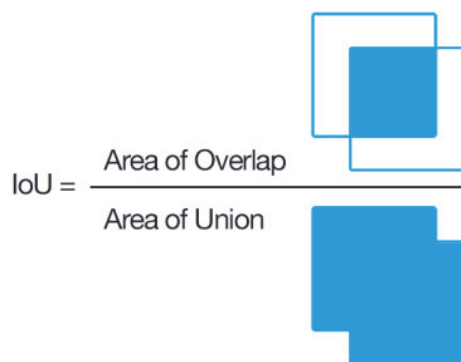


Figure 9 Schematic diagram of IOU

Finally, the filtered foreground image is placed on the blackboard image as shown in Fig. 10.

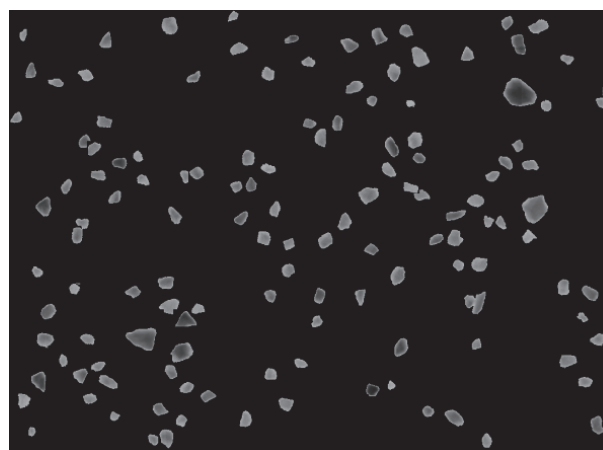


Figure 10 Sketch map of foreground distribution and filtering effect

4. Foreground and Scene Fusion: Based on the foreground distribution map in Fig. 10, the main steps are as follows.

The distribution foreground plot is binarized and negated directly as a mask. Mainly because the foreground distribution is placed in the blackboard image, it is very pure, so it can be directly used as a mask after binarization, and the inversion is mainly because the main function of this mask is to retain the background part.

b. The background image is based on the previous step mask to do its own bitwise addition operation, and obtain a background image with an object position of 0 (all black) and other background parts as background grayscale, as shown in Fig. 11.

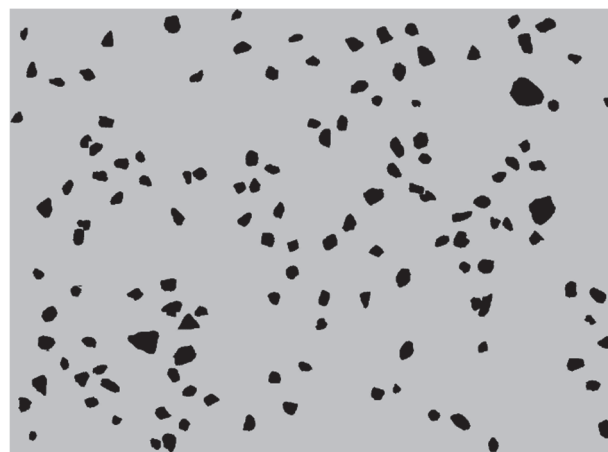


Figure 11 Background map of empty object position

c. Fig. 10 and Fig. 11 directly perform additive operations (the gray value of the object position in the background image is 0, the rest is the background grayscale, the background part in the foreground image is 0, and the specific object distribution at the object position) is obtained to obtain the generated data image, as shown in Fig. 12.

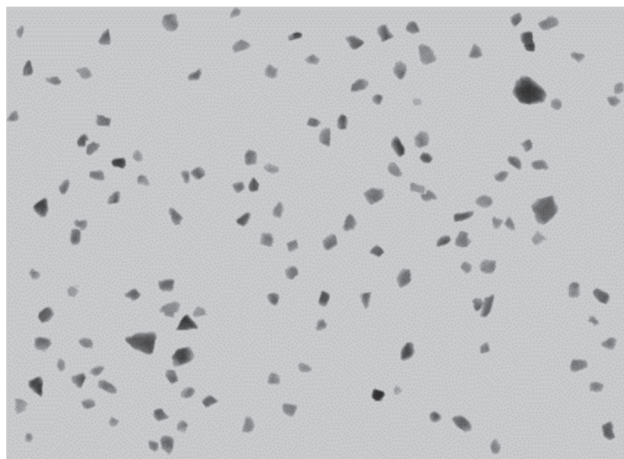


Figure 12 Effect image of foreground and background fusion

5. Label generation. Generate different data labels according to different requirements, such as the YOLO series model, the data label type is txt, and the label style is (cls, x, y, w, h) , where cls represents the category number, x, y represents the coordinates of the center point, w, h represents the width and height of the image, and (x, y, w, h) is normalized. The resulting image and label are labeled and displayed, as shown in Fig. 13.

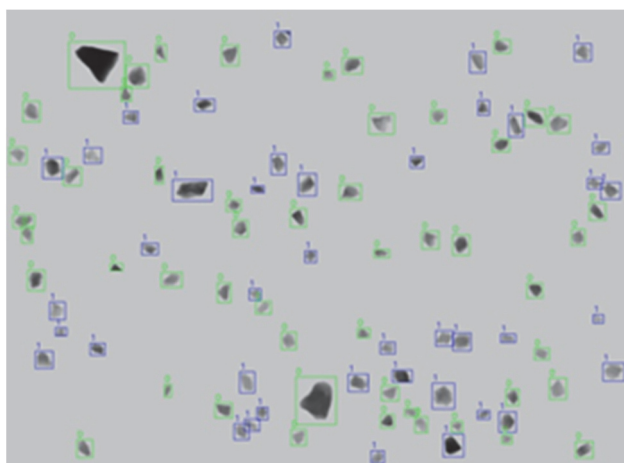


Figure 13 Schematic diagram of automatic gangue data annotation effect

The test shows that it takes 1 minute and 7 seconds to generate 1000 pictures and txt format annotation files, which is much higher than manual data annotation. At the same time, when the data volume and diversity of the single sample database are sufficient, the label data obtained by this generation method will play a positive role in the generalization of model training in theory because of its high randomness in distribution, angle, and quantity.

Above all, we get the following information.

(1) At present, the definition of the identification characteristics of coal gangue is mostly based on the idea of test statistics. The numerical distribution range of one or more characteristics of coal gangue is obtained, and the

difference between the two is found as the identification criteria. There is a problem of incomplete analysis and understanding of the characteristics of coal gangue. In order to improve the accuracy of coal gangue identification, it is necessary to further study the differences of their characteristics.

(2) Research on identification methods of coal gangue that meet the requirements of green development of coal mines. In our country, most coal resources are concentrated in Midwest areas where water resource is lacking. Identifying coal gangue using liquid media and realizing coal gangue separation has brought about the increasing pressure of water resource supply and the problem of water resource waste. With the implementation of the green clean and efficient utilization plan of coal, it is necessary to research coal gangue identification methods conforming to the requirements of green coal mine development. The application of coal gangue identification method in underground mine can promote the development of dry separation technology of coal gangue, avoid the accumulation of gangue on the ground, and contribute to the construction of clean and low-carbon development system of coal.

(3) Research on fast and efficient image recognition methods for coal gangue. Image recognition method of coal gangue is a hot research topic at present. In practical applications, environmental changes, gangue types, equipment performance and other factors will affect the image recognition results of gangue, so it is necessary to consider the generalization and usability of image recognition algorithm. Aiming at the problem that the image data of coal gangue are few and cannot be comprehensively and accurately analyzed and understood, it is an important way to build a large-scale image database of coal gangue. On this basis, the expression of coal gangue image features in deep convolutional neural network is deeply understood through coal gangue feature analysis and visualization analysis, and deep convolutional neural network suitable for coal gangue recognition is studied, which is conducive to realizing fast and efficient image recognition.

(4) Research on efficient identification method of new coal gangue. By studying photoelectric, ray recognition, image recognition, deep learning and other technologies, researchers have applied them in the field of coal gangue recognition, but there are still different problems in practical application. It is necessary to study new efficient identification methods of coal gangue, integrate and innovate on the basis of existing methods, and apply them to practice for testing, so as to improve the identification efficiency of coal gangue and the intelligent level of coal gangue separation.

4 CONCLUSION

According to the extremely pure background of dual-energy X-ray images, this paper designs an automatic data annotation method for gangue based on dual-energy X-ray. This method uses a single type of radiograph background to remove, then the foreground is purified and cut to establish a single sample library. Based on this sample library, the labeled data with coal and gangue are generated.

It needs to be clear that in the construction of the

monomer sample library, different X-ray needs to be treated differently, such as the use of dual-energy X-ray in many applications. In the sample database, we need to establish samples for high energy and low energy data respectively. When necessary, we need to do a good job in conjunction to ensure that we can obtain the data of a sample of multiple energy at the same time.

The limitation of this paper is only to collect images of coal stone under static conditions, and it does not provide a good method for objects under moving conditions. At the same time, there are many shortcomings, such as low versatility, the need to manually divide a batch of samples in advance, and the need to lay coal gangue to prevent stacking during the sampling process. In the future, more research is needed to improve. In the future, this method can be applied to other image annotation tasks with relatively pure background. In the field of coal gangue, it is an attempt to use X-ray to collect data, suggest the establishment of coal gangue sample database, and establish data annotation by image generation.

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