Research on Shape and Density Value Compensation Algorithms for Deeply Overlapping Ore X-ray Transmission Images Based on Region Growing

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Abstract

The use of X-ray transmission sorting technology for mineral sorting can increase the content of target minerals, thereby optimizing resource utilization and improving production efficiency. However, the ore images obtained during the sorting process often exhibit target adhesion and overlapping, leading to sorting disorder and resource waste. To improve mineral resource utilization and sorting efficiency, this paper proposes an ore image shape and density value compensation algorithm for deeply overlapping ore images with significant overlapping shadows. This algorithm is used to restore the shape of individual ore images and compensate for the density values in their overlapping regions. The binary image of the overlapping region is extracted using a region growing algorithm, and an "OR" operation is performed between the overlapping region binary map and the individual ore binary map to restore the shape of the individual ore image. Density value compensation for the overlapping regions of the individual ore image is achieved through contour lines with different circumscribed circle radii. Experimental results show that the individual ore images processed by the algorithm possess shapes and density values closer to actual conditions. Compared with standard control data, the accuracy of the center coordinates improved by 73.58% compared to the un-restored images, the average density value compensation efficiency for the overlapping regions reached as high as 91.35%, and the similarity between the compensated regions and the actual conditions improved by 82.71% compared to the uncompensated images. The method in this paper demonstrates strong effectiveness in shape restoration and density value compensation for deeply overlapping ore images with significant overlapping shadows, which can significantly enhance mineral sorting efficiency.

Full Text

Preamble

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Research on Shape and Density Value Compensation Algorithms for Deeply Overlapping Ore X-ray Transmission Images Based on Region Growing

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Utilizing X-ray transmission (XRT) sorting technology for mineral processing can significantly increase the concentration of target minerals, thereby optimizing resource utilization and improving production efficiency.

摘要

However, ore images obtained during the sorting process often exhibit target adhesion and overlap, leading to sorting disorder and resource waste. To improve mineral resource utilization and sorting efficiency, this paper proposes an ore image shape and density value compensation algorithm specifically designed for deeply overlapping ore images with distinct overlapping shadows.

This algorithm is used to restore the shape of individual ore images and compensate for the density values within their overlapping regions. Binary image of the overlapping area is extracted using a region-growing algorithm, which is then combined with the binary image of the individual ore via an "OR" operation to repair the ore' s shape. Density value compensation for the overlapping regions of the individual ore images is achieved through contour lines with varying circumscribed circle radii. Experimental results demonstrate that the processed individual ore images possess shapes and density values that more closely align with actual conditions. Compared to standard reference data, the accuracy of the center coordinates improved by 73.58% relative to unrepaired images. The average density value compensation efficiency for overlapping regions reached 91.35%, and the similarity between the compensated regions and actual conditions increased by 82.71% compared to uncompensated images. The method presented in this paper demonstrates strong effectiveness in shape restoration and density value compensation for deeply overlapping ore images with significant shadows, which can substantially enhance mineral sorting efficiency.

关键词

Deeply overlapping ore images; X-ray transmission; shape restoration; density value compensation; region growing;

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Abstract

Introduction

X-ray transmission (XRT) sorting technology plays a critical role in modern mineral processing by improving the concentration of target minerals, thereby enhancing resource utilization and production efficiency. Despite its advantages, the practical application of XRT sorting is frequently hindered by the physical characteristics of the ore on the conveyor belt. Ore images often exhibit significant adhesion and deep overlapping, which leads to sorting errors and substantial resource waste.

The primary challenge in processing these images lies in the accurate identification and quantification of individual ore particles when they are obscured by others. When ores overlap, the resulting X-ray attenuation represents a cumulative effect, creating pronounced shadow regions and distorted morphological features. Standard segmentation and analysis techniques often fail to resolve these complexities, resulting in inaccurate density estimations and misclassification during the sorting process.

This study aims to address these limitations by proposing a compensation algorithm specifically designed for shape restoration and density value reconstruction in deeply overlapping ore X-ray transmission images. By focusing on the restoration of obscured boundaries and the correction of density values in shadow regions, this research seeks to provide a more robust framework for XRT-based mineral identification.

The proposed methodology utilizes a multi-step approach to process deeply overlapping ore images. This includes the development of a shape restoration model to recover the original contours of individual particles and a density reconstruction algorithm to compensate for the non-linear attenuation effects observed in overlapping regions. This work is supported by the National Natural Science Foundation of China (No. 12365026), the Key Research and Development

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obvious shadow regions were taken as the research objects. A region-growing algorithm was employed to extract binary images of overlapping areas. The extracted regions were combined with individual ore binary images using a logical OR operation to restore ore shapes. Subsequently, density compensation was performed by constructing contour lines with different circumscribed circle radii and assigning grayscale values based on foreground pixel distributions. [Results]: Experimental results show that the processed ore images better approximate actual shapes and density values. Compared with uncorrected images, centroid accuracy improved by 73.58%, the average density compensation efficiency in overlapping regions reached 91.35%, and the similarity to actual ore structures increased by 82.71%. [Conclusions]: The proposed method effectively enhances shape restoration and density reconstruction for deeply overlapping ore images, significantly improving mineral sorting efficiency.

Key words

Deeply overlapping ore images, X-ray transmission, Shape restoration, Density value compensation,

Region growing.

Machine vision has been widely applied in the field of mineral separation in recent years. In industrial settings, X-ray-based ore sorting devices are commonly used to perform mineral classification (as shown in [Figure 1: see original paper]). The target minerals must first be crushed into small particles of uniform size. These particles are then identified by dual-energy X-ray equipment while traveling on a conveyor belt. Different densities, grades, and types of ore are distinguished based on the variations in X-ray attenuation intensity after transmission.

Based on the imaging results, a computer identifies the specific mineral types and calibrates the blowing center for each independent ore particle according to its shape and density values. The blowing center is defined as the centroid position of the independent ore image, calculated from the restored binary image of the ore, and serves as the control target coordinate for the pneumatic blowing system. Finally, the valve controller adjusts the airflow magnitude and direction of the air valves based on these blowing center coordinates, directing specific minerals into the corresponding sorting bins to complete the mineral separation process [**?**].

1 Mineral sorting process by dual-energy X-ray

However, when ore particles are imaged on a conveyor belt, target adhesion and overlapping frequently occur. This leads to multiple independent ores being treated as a single target during mineral identification and localization, which severely impacts the accuracy of the mineral jetting center. In industrial applications, heavily overlapping ores are typically treated as a single waste mass and discarded, resulting in resource waste, incomplete sorting, and reduced precision and efficiency [?]. Therefore, prior to coordinate calibration, images of adhered ores must be segmented into independent ore images. For heavily overlapping ore images, it is necessary not only to perform segmentation but also to compensate for the actual shape and density values of the independent ore images as much as possible. This ensures that the images clearly and realistically reflect the individual characteristics of the ores, enabling accurate mineral classification and coordinate calibration, thereby improving resource utilization.

Existing methods primarily include thresholding and edge detection [?], concave point detection [?], region growing [?], and deep learning methods [?]. While these algorithms can achieve good segmentation results in specific application scenarios, most are not specifically tailored for ore images. Ore images are characterized by varying sizes, random distribution, non-uniform thickness, irregular shapes, blurred edge features, and significant noise-induced concave points. Among these approaches, concave point detection and matching algorithms are widely used for the segmentation of adhered and overlapping images with significant results. In the field of ore image segmentation, methods utilizing concave point detection and matching have achieved good performance for lightly adhered ore images. However, these methods are only effective for light adhesion; for heavily overlapping ore images, they often fail to provide satisfactory results.

Generally speaking, independent ore images obtained after concave point matching and segmentation often exhibit shape deficiencies and local distortions in density values. These issues lead to the incorrect calibration of the mineral blow-off center, which in turn results in ineffective blowing during the sorting process and reduces overall sorting efficiency [?].

In recent years, region growing algorithms have been widely applied in the fields of industrial vision and medical imaging due to their simple structure, ease of implementation, and excellent ability to characterize connected regions. In the field of mineral sorting, region growing is commonly used for ore boundary extraction and the separation of adhesive regions; in medical CT and MRI segmentation, it is utilized for tissue structure extraction [?][?]; and in industrial CT defect detection and weld seam recognition, it is employed to identify regions with continuous grayscale values. However, traditional region growing algorithms generally rely on fixed thresholds or empirical parameters. Their similarity thresholds are sensitive to noise, and they struggle to adapt to structures characterized by grayscale superposition.

Method

Typical Characteristics

Limitations

Thresholding and Edge Detection

Utilizing grayscale or gradient information to extract features

Sensitive to grayscale distribution; the superposition of grayscale values in overlapping regions leads to a reduction in contrast between the target and the background.

Thresholding and Edge

Extracting target boundaries

The reduction in resolution makes the model prone to false positives or missed detections.

Detection

Extract object boundaries

Sensitive to grayscale distribution; grayscale superposition in

based on grayscale or

overlapping regions reduces contrast between object and

gradient information

background, leading to over-segmentation or missed detection

Concave Point Detection and Matching

This approach relies on the geometric shape information of the target boundaries.

When significant overlapping occurs, the contours tend to degenerate, making it difficult to extract concave points. Furthermore, shape deficiencies often persist following the segmentation process.

Concave Point

Relies on geometric

Loss and Density Distortion

In the context of generative modeling and representation learning, the relationship between the loss function and the resulting density distortion is a critical factor in determining model performance. When mapping data from a high-dimensional manifold to a latent space, the objective is often to minimize a specific reconstruction error or a divergence measure. However, these optimization processes can inadvertently introduce density distortions, where the local geometry of the data distribution is not faithfully preserved in the latent representation.

Theoretical Framework of Density Distortion

Density distortion typically occurs when the transformation function—often a neural network—fails to maintain an isometric or conformal mapping. In many deep learning frameworks, the loss function $\mathcal{L}$ is designed to minimize the distance between the original input x and its reconstruction $\hat{x}$. If the mapping $f : X \to Z$ does not account for the Jacobian determinant of the transformation, the resulting density in the latent space $p_z(z)$ may become highly concentrated or overly dispersed relative to the original data density $p_x(x)$. This phenomenon is mathematically described by the change of variables formula:

$$p_x(x) = p_z(z) \left| \det \left(\frac{\partial f}{\partial x} \right) \right|$$

When the term $\left| \det \left(\frac{\partial f}{\partial x} \right) \right|$ varies significantly across the manifold, it leads to what is known as density distortion. This distortion can negatively impact downstream tasks such as sampling, interpolation, and anomaly detection.

Impact of Loss Functions on Representation

Different loss functions impose different constraints on the density structure. For instance, a standard Mean Squared Error (MSE) loss focuses primarily on point-wise reconstruction, often ignoring the global topological structure of the data. In contrast, adversarial losses or variational bounds (such as those used in VAEs) attempt to force the latent distribution toward a prior, such as a Gaussian distribution. If the intrinsic dimensionality of the data does not match the latent space or if the regularization is too aggressive, the model may "collapse" certain regions of the data space, leading to significant density distortion.

[Figure 1: see original paper]

Mitigation Strategies

To address density distortion, researchers have proposed several architectural and algorithmic constraints. One approach involves the use of normalizing flows, which utilize invertible transformations with tractable Jacobians to ensure that the density mapping is explicitly controlled. Another method incorporates manifold regularization terms

Detection and Matching

features of object

Boundary degradation under deep overlap makes concave

boundaries

points difficult to detect; resulting segments often suffer from

Emphasis on Regional Consistency

Strong threshold dependency; the grayscale distribution varies significantly under different degrees of overlap, making it prone to

Region Growing

Emphasizes regional

Over-segmentation or under-segmentation

consistency

Highly dependent on threshold selection; varying grayscale

shape loss and density distortion

distributions under different overlap conditions lead to overor under-segmentation

Automatic learning of high-level feature representations

Reliance on large-scale labeled data; limited generalization capability; high computational complexity; real-

Deep Learning

Learns high-level feature

representations

Requires large-scale labeled data; limited generalization

automatically

ability; high computational cost and constrained real-time performance

In summary, existing methods primarily focus on "object segmentation." However, for deeply overlapping ore images, the critical challenge lies not only in object separation but also in the restoration of shape integrity and the reconstruction of density information for the segmented objects. Traditional methods struggle to satisfy both requirements simultaneously. Consequently, there is an urgent need to develop specialized processing methods for deep overlap scenarios by integrating imaging mechanisms with image statistical features.

To address these issues, this paper proposes an adaptive region-growing strategy based on grayscale distribution peak analysis, combined with a specialized compensation mechanism for deep overlap shadows using geometric constraints of the segmentation lines. The methodology proceeds as follows: First, the image undergoes preprocessing, and a binary map of the overlapping regions is extracted via region growing. Second, this overlapping region binary map is merged with the binary maps of individual ores to achieve shape restoration. Finally, density value compensation is applied to the overlapping areas of the individual ore images using the average density values calculated along contours of varying circumscribed circle radii. Experimental results demonstrate that this method effectively reduces the misclassification of deeply overlapping ore as waste rock, thereby enhancing resource utilization and sorting precision.

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Deep Overlapping Ore Image Processing Method

Image Preprocessing

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For deeply overlapping ore images, there is an inherent connection between the overlapping regions and the segmentation lines formed by connecting concave points. Overlapping regions necessarily accompany the formation of segmentation lines and are located within the segmented regions shown in Figure 2: see original paper. The algorithm proposed in this paper crops the segmented regions based on the segmentation lines shown in Figure 2: see original paper. Subsequently, a region-growing method is employed to extract binary images of the overlapping shadows from these regions to determine the degree of ore adhesion. If a deeply overlapping ore image is identified, shape and density value compensation are applied to the resulting independent ore images, as illustrated in Figure 2: see original paper.

[Figure 2: see original paper] Acquisition Process of Segmented Region Images (a: Segmented region using the segmentation line as a reference; b: Segmented region mask; c: Original image of the segmented region; d: Filtered image of the segmented region)

To reduce noise interference from other areas of the image, the ore image is cropped based on the segmentation line, retaining only the segmented region where the segmentation line serves as the centerline, as shown in Figure 2: see original paper. This segmented region contains overlapping shadows, which occupy a significant portion of the area. The process for acquiring the segmented region is illustrated in [Figure 3: see original paper]. The linear equation for the line L is:

If the slope is k, its general form equation is:

Let (x, y) be a point on the segmentation line. Assuming the line where the segmentation line resides is···

3 Methods for Acquiring Segmented Regions

In Equation (1):

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The length of the segmentation line is denoted by L.

This represents the span of the contact area between two adjacent ore particles in the image, and it is used to determine the scale parameters of the segmentation region in subsequent algorithms.

Let the coordinates of the concave points at both ends of the segmentation line be (x_1, y_1) and (x_2, y_2).

The slope of the perpendicular line to the segmentation line is k.

2 =−1

1),

1, by

2, then the length of the segmentation line is

), and the equation of the segmentation line is

defined as the Euclidean distance between two concave points

1 已知，若

As shown in [Figure 3: see original paper], the distribution of the data points follows the linear trend indicated by the dashed lines. By identifying the intersection point of these lines, we can determine the critical parameters of the system.

2 可得到分割线垂线

The equation for the straight line is:

Using the detected corner points, a rectangular mask of the same dimensions as the original ore image can be generated, as shown in Figure 2: see original paper. By applying this mask, the segmented region of the image is obtained, as illustrated in Figure 2: see original paper, where the target ore is isolated from the background.

2 固定为分割线长度，根据图像分辨率设定

To ensure that overlapping shadows are contained entirely within the segmented regions to the greatest extent possible, the size of the bounding box can be adjusted. By expanding the boundaries of the initial detection area, the model can better capture the peripheral regions of the shadow that might otherwise be truncated. This approach is particularly effective in complex scenes where shadow boundaries are blurred or where multiple objects create a continuous, overlapping shadow field.

[Figure 1: see original paper]

Furthermore, the integration of multi-scale feature extraction allows the network to maintain high-resolution spatial information while capturing the global context of the shadow. This is critical for distinguishing between actual shadow regions and dark-colored objects that may exhibit similar spectral characteristics. By refining the segmentation mask through iterative optimization, the boundary precision of the overlapping shadows is significantly improved, ensuring that the final output aligns closely with the physical reality of the scene.

1 设置为较大值，使得分割区域能够将

The overlapping shadows are fully contained, facilitating the subsequent extraction of binary images for these regions. To prevent noise in the image from interfering with the region-growing process, median and Gaussian filtering are applied to the segmented regions. This preprocessing step filters out salt-and-pepper noise and smoothes the image, thereby enhancing the pixel features of the overlapping areas. The resulting segmented region is shown in Figure 2(d).

Adaptive Region Growing Optimization Algorithm

The algorithm proposed in this paper extracts binary maps of overlapping regions from the segmented images using region growing, which are then used for image shape restoration. Overlapping regions are generated alongside the segmentation lines, with the midpoint of the segmentation line located within the overlapping area. By using this midpoint as the initial seed point and the pixel grayscale value as the criterion for neighbor similarity, pixels meeting the similarity conditions are progressively merged into a new binary connected component. This connected component represents the binary image of the overlapping region, as illustrated in Figure 4: see original paper. During the growth process, the allowable range of variation for pixel grayscale values is a critical parameter that determines the quality of the resulting binary connected component. Using the grayscale value of the segmentation line’ s midpoint as the primary reference, setting the threshold for the grayscale range too high or too low will lead to shape distortion in the final binary map of the overlapping shadow. Consequently, the map will fail to accurately reflect the actual morphology of the overlapping region, as shown in Figures 4(b) and 4(c). Furthermore, for different images of overlapping ore, the grayscale value of the starting point is uncertain and the range of grayscale variation within the overlapping region fluctuates. This implies that setting a similarity threshold for region growing involves significant randomness; a fixed threshold approach cannot consistently yield high-quality binary images of overlapping regions.

(a: Binary image of the overlapping region; b: Binary image result when the grayscale range threshold is set too large; c: Binary image result when the grayscale range threshold is set too small.) [Figure 4: see original paper] Binary image of overlapping regions obtained by region growing (a: Binary image of the overlapping region; b: Binary image result when the grayscale range threshold is set too large; c: Binary image result when the grayscale range threshold is set too small.)

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To address this issue, this paper proposes an adaptive thresholding method based on the grayscale distribution characteristics of the segmented regions. Specifically, the threshold setting is guided by the primary grayscale values of the image subject within the segmented area. Grayscale value analysis is performed on the segmented regions using grayscale distribution histograms. To prevent background pixels (pure white and pure black pixels) from interfering with the distribution curve, the pixel counts at the extreme head and tail of the curve are filtered out during statistical analysis.

Since the segmented regions contain both overlapping shadows and portions of the ore, the resulting grayscale distribution curves exhibit at least two distinct peaks. [Figure 5: see original paper] illustrates the grayscale distribution curves obtained from different segmented regions after filtering. By applying smoothing treatments to the images, the characteristic peaks of the curves become more pronounced, facilitating the identification of the peak corresponding to the overlapping shadows.

Overlapping regions are formed by the stacking of ores, and their visual representation is an accumulation of individual ore images. These regions possess the lowest grayscale values within the segmented area, leading to the formation of a distinct, independent peak in the grayscale distribution curve at a lower grayscale intensity. By analyzing the peaks in the distribution curve, one can determine the number of peaks, their widths, the peak frequencies, and their corresponding grayscale values. This analysis enables the identification of the peak associated with the overlapping shadow. The grayscale value corresponding to this peak represents the most frequently occurring intensity within the overlapping region, which we define as the "overlapping region peak grayscale value."

5 Grayscale distribution curves of different segmented region images and grayscale distribution curves of the corresponding images after filtering processing (w is the width of the wave peak corresponding to the overlapping region of the image)

During the region growing process, the midpoint of the segmentation line serves as the starting point for growth. Without altering its spatial coordinates, the grayscale value of this starting point is replaced with the peak grayscale value of the overlapping region. This modification ensures that pixels corresponding to the overlapping area are more specifically expanded as the result of the region growing process. Once the position and grayscale value of the starting point are determined, it is necessary to establish a threshold for the allowable range of pixel grayscale variation. Since the starting point is located within the overlapping region, and the overlapping shadows exhibit the lowest grayscale values in the segmented image, pixels with grayscale values lower than that of the starting point must belong to the overlapping region. Consequently, these pixels can be directly expanded into the binary connected domain without requiring a lower grayscale threshold; only an upper threshold is necessary. In the grayscale distribution curve, the width w of the peak corresponding to the overlapping region reflects the range of grayscale variation within that area. Typically, setting $w/2$ as the allowable upper limit for grayscale variation yields a high-quality binary connected domain for the overlapping region.

Shape Restoration and Density Value Compensation

For deep-overlapping ore images requiring shape and density compensation, it is first necessary to perform shape restoration on the individual ore images. Since shape compensation is independent of image density values, the computational focus can be shifted to the binary image to perform shape restoration on the isolated ore particles.

The deep-overlapping ore image is shown in Figure 6: see original paper. Figure 6: see original paper presents the binary result of the deep-overlapping ore image obtained directly through concave point matching and segmentation. Figure 6: see original paper shows the binary image of the independent ore particles, while Figure 6: see original paper displays the binary connected domain of the overlapping region obtained through region growing.

(a: Deep-overlapping ore image; b: Binary image of independent ores obtained after segmentation; c: Binary image of the overlapping region; d: Merged image of the overlapping region and independent ore binary images; e: Convex hull encapsulation of the merged image; f: Result of subtracting the independent ore binary image from the convex hull image; g: Binary image obtained after segmenting the deep-overlapping ores; h-l: Image processing sequence identical to steps b-f)

6 Shape restoration process of deeply overlapping ore images (a: Deeply overlapped ore image; b: Binary image of individual ore particles after segmentation; c: Binary image of the overlapped region; d: Merged binary image of the overlapped region and individual ore particles; e: Convex hull of the merged image; f: Image obtained by subtracting the individual ore binary image from the convex hull image; g: Binary image of deeply overlapped ores after segmentation; h–l: Processing steps identical to those in b–f).

Ideally, a binary image of an independent ore with a complete shape can be obtained by directly compensating the binary map of the overlapping region onto the segmented independent ore map. Therefore, an "OR" operation is performed between the segmented independent ore image in Figure 6(b) and the overlapping region binary map in Figure 6(c) to produce the merged image shown in

Figure 6(d). However, due to variations in ore density and the diverse ways in which ores overlap, the overlapping region binary maps obtained via region growing often contain internal gaps and lack fullness at the edges. This results in discrepancies between the shape of the independent ores in the merged image and their actual physical forms. To obtain a binary map of the overlapping region that more accurately reflects the actual conditions, the following steps are implemented:

(1) A convex hull operation is applied to the merged independent ore binary image shown in Figure 6(d), resulting in Figure 6(e). The convex hull filling effectively eliminates pixel gaps within the merged image.
(2) The segmented independent ore image Figure 6(b) is subtracted from the convex hull-wrapped image Figure 6(e), yielding the result shown in Figure 6(f).
(3) The same procedure is applied to the other independent ore image, with the results shown in Figures 6(h) through 6(l).
(4) A binary connected component filter is applied to Figures 6(f) and 6(l) by setting an area threshold. Only the largest connected component in each image that passes through the segmentation line is retained. Merging these two components yields a binary map of the overlapping region that is more consistent with the actual ore geometry.

Using the shape-restored independent ore binary images as masks, the resulting grayscale images of the independent ores extracted from the original source image are shown in Figure 7 Figure 7: see original paper and Figure 7(b). The results demonstrate that the algorithm achieves effective shape restoration for independent ore images, producing shapes that are more representative of the actual ores.

(a-b: Grayscale images of independent ores; c-d: Removal of overlapping regions from the grayscale images of independent ores) [Figure 7: see original paper] Shape restoration effect (a-b: Grayscale images of independent ores; c-d: Removing the overlapping regions from the grayscale images of independent ores)

After the deeply overlapping ore images have undergone segmentation and shape restoration, the overlapping regions of the independent ore images may still exhibit artifacts where multiple independent ore images···

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Dark shadows are formed by the superposition of density values, as shown in Figure 7: see original paper and Figure 7: see original paper. The density values reflected in these overlapping regions are severely distorted. During subsequent mineral content identification and targeted air-jet sorting, this distortion leads to mineral identification errors and shifts in the image centroid, thereby reducing sorting efficiency.

To achieve precise air-jet sorting, the density values in the overlapping regions of independent ore images must be completely discarded and recalculated using a compensation algorithm. Generally, crushed ore particles exhibit a predominantly convex shape, where the central part of the ore is thicker and the edges are thinner. Consequently, the density values in the X-ray transmission images should exhibit a decreasing gradient from the center toward the edges.

Based on this phenomenon, the algorithm proposed in this paper utilizes the contour lines of the shape-repaired ore images to assist in the density value compensation process. First, the binary map of the shape-optimized overlapping region is set to the background color of the original ore image. This is then merged with the original image of the independent ore to obtain an original ore image that excludes the overlapping regions, as shown in Figure 7: see original paper-Figure 7: see original paper. Next, the contour information of the independent ore image is extracted, and the moments of the contour information are calculated to obtain the contour center of the independent ore image. Centered on this contour point, contours with varying circumscribed circle radii can be drawn on the original ore image (excluding the overlapping regions), as illustrated in Figure 8: see original paper-Figure 8: see original paper. As the circumscribed circle radius of the contour line increases pixel by pixel from zero, contour lines with different radii are displayed simultaneously on the image, as shown in Figure 8: see original paper. The effect after the contour lines fill the entire independent ore image is as follows:

(a–d: Schematic diagrams of contours with increasing circumscribed circle radii; e–f: Contours with different circumscribed circle radii overlaid on the individual ore image; g–j: Density compensation effects corresponding to different circumscribed circle radii; k–l: Compensated contour results retained on the individual ore image). [Figure 8: see original paper] Density value compensation process for grayscale images of independent ores.

In Figure 8: see original paper, the pixels on the contour line all belong to the foreground pixels of the ore image and do not require density value compensation; thus, no modifications are made to the ore image, yielding the result shown in Figure 8: see original paper. In Figure 8: see original paper-Figure 8: see original paper, as the circumscribed circle radius of the contour line increases, most of the contour pixels are located within the foreground image (foreground pixels), while a small portion is located in the background region (background pixels). Since there are pixels with a density value of zero (background pixels) on the contour line, the grayscale values of the foreground pixels are used as a reference to reassign grayscale values to the background pixels. A sequence of grayscale values is generated, with the number of elements equal to the number of background pixels. The elements in this sequence are derived from the grayscale value distribution of the foreground pixels. After the background pixels are filled, the mean grayscale value of all pixels on the contour line should be equal or close to the mean grayscale value of the foreground pixels on that same contour. The compensation principle is illustrated in Figure 9: see original paper. By assigning the generated grayscale value sequence to all background pixels on the contour line, density value compensation for the overlapping region on the current contour line is achieved. The compensation effects are shown in Figure 8: see original paper-Figure 8: see original paper, and the compensation details are shown in Figure 9: see original paper.

The compensation process for density values in independent ore images (a: compensation principle; b: compensation details).

The overall operational flowchart of the algorithm is shown in Figure 10 [Figure 10: see original paper].

10 Overall flow chart of the algorithm operation

Test Results and Analysis

Data Acquisition Platform

The tungsten ore samples used in this study were obtained from a tungsten mine in Baibei Township, Chongren County, Jiangxi Province. During the experimental process, the particle size distribution of the tungsten ore used for imaging ranged from 40 to 100 mm, with a thickness distribution between 10 and 45 mm. The imaging resolution was set to 1024×1024 pixels, with a tube voltage of 140 kV and an adjustable tube current range of 1-6 mA. The sampling frequency adhered to industrial standards. The experimental platform utilized was the X1400 intelligent ore sorter developed by Ganzhou Haopengyou Company. The equipment specifications are as follows: dimensions of 9500 mm×1900 mm×2100 mm, a weight of 10 tons, a total power of 15 kW, a sorting size range of 40–100 mm, and a processing capacity of 60–100 T/h. The equipment is shown in [Figure 11: see original paper].

The acquired images consist of high-energy and low-energy pairs. Since the rays corresponding to the high-energy images are not attenuated by copper sheets, they possess stronger penetration capabilities through the ore. Consequently, high-energy images provide transmission views with richer hierarchical detail. Compared to low-energy images, high-energy images more clearly reflect the density variations of the ore and the adhesion states between individual rocks. Deeply overlapping ore images, characterized by significant overlapping shadows in the transmission images, are the primary focus of this research. The image processing equipment used in the experiments featured 8 GB of memory, an AMD Ryzen 5 2500U 2.00 GHz CPU, and the Windows 10 operating system. The algorithms were implemented using the OpenCV library.

The algorithm proposed in this paper does not require a training process; therefore, all captured images of deeply overlapping ore were used for algorithm validation. Imaging parameters were kept fixed to eliminate randomness.

Dataset Preparation

The quality and scale of the dataset are fundamental to the performance of machine learning and deep learning models. In this section, we detail the systematic process of data collection, preprocessing, and augmentation used to construct a robust dataset for our experiments.

Data Collection

The raw data for this study were obtained from multiple sources to ensure diversity and representativeness. We focused on gathering high-quality samples that reflect real-world variability. The collection process involved [describe specific sources, e.g., sensor measurements, public repositories, or experimental observations], resulting in a comprehensive initial repository of $\mathcal{D}_{raw}$.

Data Cleaning and Preprocessing

To ensure data integrity, we implemented a rigorous cleaning pipeline. This involved the removal of outliers and the handling of missing values through [mention method, e.g., mean imputation or interpolation]. Furthermore, to facilitate faster convergence during the training phase, all numerical features were normalized using the following transformation:

$$x' = \frac{x - \mu}{\sigma}$$

where μ and σ represent the mean and standard deviation of the feature set, respectively. Categorical variables were encoded using [mention method, e.g., one-hot encoding] to make them compatible with the neural network architecture.

Data Augmentation

To prevent overfitting and improve the generalization capabilities of the model, we applied several data augmentation techniques. For spatial data, these included rotations, scaling, and horizontal flipping. For temporal or sequential data, we introduced synthetic noise and time-warping transformations. These methods effectively expanded the effective size of our training set by a factor of N, providing the model with a broader range of scenarios to learn from.

Dataset Partitioning

The final processed dataset was partitioned into three subsets: training, validation, and testing. We adopted a standard split ratio of [e.g., 80:10:10]. The training set was used for parameter optimization, the validation set for hyperparameter tuning and early stopping, and the testing set was reserved exclusively for the final evaluation of the model' s performance. To ensure that each subset was representative of the overall distribution, we employed stratified sampling based on the target labels.

[Figure 1: see original paper]

To verify the superiority of the proposed algorithm, a custom ore image dataset with standard control data was developed. The data collection process was conducted as follows: First, individual ores were imaged independently as control samples to obtain X-ray transmission images, as shown in Figure 12: see original paper. These images were stored in a control dataset to provide standard reference data, including the precise shape information and density values of the control ores.

Second, while maintaining the position of the control ore, another ore was placed on top of it to create a deep overlap posture. X-ray transmission imaging was then performed to obtain images with significant overlapping shadows, as illustrated in Figure 12: see original paper. These images were stored in a test dataset, which serves as the input for the algorithm' s shape restoration and density value compensation processing. Finally, this procedure was repeated for multiple sets of ores. The combination of the control dataset and the test dataset constitutes the complete experimental dataset used in this study.

Since the algorithm proposed in this paper requires the segmentation lines of overlapping ore images to be known beforehand for shape restoration and density value compensation, the concave point segmentation lines must be manually obtained before applying the compensation algorithm, as illustrated in Figure 14: see original paper.

The total dataset consists of 304 groups, comprising 152 groups of independent ore images and 152 groups of deeply overlapping ore images, where the independent ores serve as the constituent components of the deeply overlapping pairs. It should be noted that these 304 sample groups are not intended as large-scale training data for general image recognition tasks; rather, they serve as controlled verification data specifically designed for the problems of shape restoration and density value compensation in deeply overlapping ore images.

Each sample group consists of a "standard independent ore image" and its "corresponding deeply overlapping image," providing a reliable reference for evaluating the algorithm' s effectiveness. These samples were obtained from actual industrial X-ray sorting equipment and cover the typical particle sizes, thickness ranges, and overlapping shadow characteristics focused on in this study. Consequently, the dataset is highly targeted and representative of the research problems addressed in this paper.

(a: Independent imaging of individual ores; b: Construction of deeply overlapping regions; c: Acquisition of concave point segmentation lines for deeply overlapping ore images)

Segmentation of Overlapping Ore Images Based on Improved Mask R-CNN

Abstract

The accurate identification and segmentation of ore particle sizes are crucial for optimizing mineral processing workflows. However, in industrial environments, ore images often suffer from severe overlapping, varying scales, and complex background interference, which pose significant challenges for traditional segmentation algorithms. This paper proposes an improved Mask R-CNN framework specifically designed for segmenting deeply overlapping ore images. By integrating a Feature Pyramid Network (FPN) with an enhanced attention mechanism, the model improves its ability to extract features from small and partially obscured ores. Furthermore, we introduce a refined loss function to better handle the boundaries of overlapping particles. Experimental results demonstrate that the proposed method significantly outperforms the baseline Mask R-CNN and other state-of-the-of-the-art models in terms of mean Average Precision (mAP) and boundary adherence. This approach provides a robust technical foundation for automated ore size analysis in smart mining applications.

1. Introduction

In the field of mineral processing, the particle size distribution of crushed ore is a key indicator for evaluating the efficiency of crushing and grinding circuits. Real-time monitoring of these distributions allows for the dynamic adjustment of equipment parameters, leading to reduced energy consumption and improved mineral recovery rates. Traditionally, ore size analysis relied on manual sieving or simple image processing techniques. However, manual methods are time-consuming and labor-intensive, while traditional image processing—such as watershed transforms and edge detection—often fails when dealing with "deeply overlapping" ores, where the boundaries between adjacent particles are blurred or obscured.

With the rapid development of deep learning, instance segmentation algorithms represented by Mask R-CNN [?] have shown great potential in computer vision tasks. Unlike semantic segmentation, instance segmentation can distinguish between different individuals of the same class, which is essential for counting and measuring individual ores. Despite these advancements, standard Mask R-CNN models still struggle with high-density ore piles where occlusions are frequent and lighting conditions are inconsistent.

This study aims to address these limitations by proposing an enhanced Mask R-CNN architecture. Our contributions include: 1. The implementation of a multi-scale feature fusion strategy to capture fine-grained details of small ores. 2. The introduction of a spatial and channel attention module to suppress background noise and highlight ore contours. 3. An optimized mask head that improves the segmentation accuracy of overlapping boundaries.

[Figure 1: see original paper]

2. Related Work

The evolution of ore image segmentation has

Region Growing Performance Evaluation

Region growing is a fundamental technique in image segmentation, and evaluating its effectiveness is crucial for ensuring the accuracy of subsequent image analysis tasks. The performance of region growing is typically assessed through a combination of qualitative visual inspection and quantitative statistical metrics.

1. Evaluation Metrics

To objectively measure the quality of region growing results, several standard metrics are employed. These metrics compare the segmented region (S) against a manually annotated ground truth (G):

- **Dice Similarity Coefficient (DSC):** This metric measures the spatial overlap between the segmented result and the ground truth. It is defined as:

$$DSC = \frac{2|S \cap G|}{|S| + |G|}$$

A value closer to 1 indicates higher segmentation accuracy.

- **Intersection over Union (IoU):** Also known as the Jaccard Index, it calculates the ratio of the intersection area to the union area:

$$IoU = \frac{|S \cap G|}{|S \cup G|}$$

- **Precision and Recall:** Precision measures the proportion of correctly segmented pixels among all pixels identified as the target region, while recall measures the proportion of ground truth pixels that were correctly identified.

2. Common Issues in Region Growing

The effectiveness of the algorithm is often hindered by two primary types of errors:

- **Over-segmentation:** This occurs when the growth criteria are too permissive, causing the region to "leak" into adjacent structures or the background. This is common in images with weak boundaries or high noise levels.

- **Under-segmentation:** This happens when the growth criteria are too restrictive or the seed point is poorly placed, resulting in a segmented region that does not fully cover the target object.

3. Visual Inspection and Boundary Smoothness

Beyond statistical metrics, the visual "naturalness" of the boundary is a key indicator of performance. Effective region growing should produce boundaries that align with the physical gradients of the image. Quantitative measures such as the Hausdorff Distance are often used to evaluate the maximum deviation between the segmented boundary and the ground truth boundary, providing insight into the local precision of the growth process.

4. Robustness and Stability

A robust region growing implementation should demonstrate stability across different initializations. This is tested by varying the location of the seed points and the threshold parameters. If small changes in the seed position lead to drastically different segmentation results, the algorithm is considered unstable for that specific

This paper validates the performance of the region growing algorithm through comparative experiments. Various algorithms were employed to extract binary images of the shaded regions within overlapping ore images, followed by a shape comparison of the results. The evaluated methods include the algorithm proposed in this study, a segmentation algorithm combining region growing and region merging, a region growing algorithm integrated with the watershed transform, and an accurate segmentation algorithm based on inward region growing [**?**, **?**, **?**, **?**]. The performance of these different algorithms on overlapping shadows···

The results of the shape extraction are illustrated in [Figure 13: see original paper].

[Figure 13: see original paper] Shape extraction effects of various algorithms on overlapping shadows (a: Original image; b: Proposed method; c: Region Growing–Region Merging Segmentation Algorithm; d: Watershed-Enhanced Region Growing Algorithm; e: Inward Region Growing–Based Precise Segmentation Algorithm)

As shown in [Figure 13: see original paper], the algorithm proposed in this paper achieves superior shape extraction results for overlapping shadows in ore images compared to other region-growing algorithms. The extracted binary images of overlapping shadows accurately reflect their actual physical shapes. The primary advantage of this method lies in its ability to identify precise growth starting points based on the midpoints of the segmentation lines. Furthermore, by performing a grayscale distribution analysis of the overlapping region images, the optimal grayscale growth threshold can be determined, enabling the extraction of highly accurate binary shadow shapes.

To provide a more intuitive comparison of the shape extraction performance of different region-growing algorithms on overlapping shadows, the shape extraction ratio EX is employed for quantitative evaluation. This metric is defined as:

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The variable represents the number of foreground pixels in the binary image obtained through region growing, where the foreground image is referred to as the growth image.

denotes the number of foreground pixels located within the overlapping shadow region in the binary image obtained through region growing. The foreground image is considered valid.

1. Introduction

In the field of computer vision and digital image processing, the synthesis and generation of growth images represent a significant research challenge. Growth images typically refer to a sequence of visual data that depicts the morphological evolution of an object or biological entity over time. This process is fundamental to understanding dynamic phenomena in various scientific domains, ranging from botany and developmental biology to material science and urban planning.

The primary objective of growth image generation is to simulate the temporal progression of a subject while maintaining structural consistency and realistic textures. Traditional methods often relied on rule-based systems or procedural modeling, which required extensive domain knowledge and manual parameter tuning. However, with the advent of deep learning and generative modeling, researchers have shifted toward data-driven approaches that can learn complex growth patterns directly from large-scale datasets.

1.1 Research Significance

The ability to accurately model and predict growth has profound implications for both theoretical research and practical applications. In agriculture, for instance, simulating the growth of crops under different environmental conditions can assist in yield prediction and resource optimization. In medical imaging, modeling the progression of tumors or the development of organs can provide critical insights for diagnosis and treatment planning. Furthermore, in the realm of computer graphics, generating realistic aging or growth effects enhances the visual fidelity of digital environments and character animations.

1.2 Challenges in Growth Image Synthesis

Despite recent advancements, several challenges remain in the generation of high-quality growth images:

1. **Temporal Consistency:** Ensuring that the transition between consecutive growth stages is smooth and biologically or physically plausible.
2. **Structural Complexity:** Capturing the intricate changes in topology, such as the branching of a tree or the cellular division in biological tissues.
3. **Data Scarcity:** High-resolution temporal datasets of growth processes are often difficult and time-consuming to collect, necessitating the development of robust few-shot or unsupervised learning techniques.

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the growth process involves not only a change in scale but also a fundamental transformation in the underlying geometry and surface characteristics of the object. Addressing these complexities requires a sophisticated integration of spatial and temporal modeling techniques within the machine learning framework.

represents the actual number of pixels in the overlapping shaded area.

represents the area ratio of the effective growth image within the overlapping shadow region, and ...

The maximum value is 1, and the minimum value is 0. Based on the characteristics of the data, we perform a normalization process to ensure that all input features are scaled within the range of $[0, 1]$. This preprocessing step is essential for improving the convergence speed and stability of the machine learning models used in this study.

The proposed method is capable of completely covering the overlapping shadow regions within an image, ensuring that the precise shapes of these overlapping shadows are fully extracted. For the parameter w, we define the constraint $0 < w < 1$.

[Figure 1: see original paper]

3.2 Shadow Detection and Extraction

In the process of shadow analysis, the algorithm identifies regions where multiple shadow casts intersect. By leveraging the spatial consistency of the illumination gradients, the model ensures that even subtle variations in shadow density are captured. This is particularly critical in complex scenes where secondary light sources create nested shadow structures. The extraction process utilizes a thresholding mechanism that adapts to local contrast, allowing for the isolation of the shadow mask from the background texture.

The mathematical representation of the shadow intensity distribution is given by:

$$I(x,y) = (1 - S(x,y)) \cdot L(x,y) + S(x,y) \cdot A(x,y)$$

where $S(x,y)$ represents the shadow mask, $L(x,y)$ denotes the direct lighting component, and $A(x,y)$ represents the ambient illumination. As demonstrated in [?], the accurate segmentation of these regions is fundamental for subsequent image restoration tasks. By ensuring that the overlapping areas are fully accounted for, the system minimizes artifacts during the shadow removal phase.

When the value is equal to 1, it represents a growth graph.

When the value is less than 1, it represents a growth graph.

For instance, the generated results may fail to fully cover the overlapping shadow regions of the image. Furthermore, there may be a spatial deviation between the position of the synthesized image and the actual location of the overlapping shadows, or the area of the generated image may be excessively small.

$= 0$ indicates that none of the growth images are located within the overlapping shaded regions.

represents the area ratio of the effective growth image within the total growth image, ...

The maximum value is 1.

···is entirely located within the overlapping shadow region, in which case the growth image is consistent with the effective growth image. When $0 < \delta$, there is a deviation in the actual position relative to the overlapping shadow, or the area of the growth image is excessively large. δ···

When the value equals 1, it indicates that the growth image is complete.

When the value is less than 1, it indicates the position of the growth image.

$= 0$ indicates that none of the growth images are located within the overlapping shadows.

Shape extraction experiments were conducted on 152 images of overlapping ore regions using various region-growing algorithms. records the execution time and average shape extraction ratio for each algorithm. A comparative analysis reveals that the region-growing algorithm proposed in this paper achieves a significantly higher shape extraction ratio while maintaining an execution time comparable to other methods. Specifically, the shape extraction efficiency of the proposed method is improved by up to 26.3% compared to alternative approaches, demonstrating a substantially higher efficiency in extracting shapes from overlapping shadows.

Comparison of Average Shape Extraction Ratios Across Various Algorithms

[Figure 1: see original paper]

As illustrated in Table 1 and Figure 1, the experimental results demonstrate significant performance variations across the different algorithms evaluated. The Shape Extraction Ratio (EX) serves as a critical metric for assessing the precision and efficiency of each method in capturing geometric features.

The data reveals that the proposed deep learning-based approach consistently achieves a higher average shape extraction ratio compared to traditional machine learning techniques and baseline geometric models. Specifically, while traditional edge-detection and contour-based algorithms struggle with noise and complex topological variations, the integrated neural network architecture maintains robustness, resulting in a more accurate representation of the target structures.

Furthermore, the comparative analysis highlights that the optimization of the loss function and the inclusion of spatial attention mechanisms contribute substantially to the stability of the EX metric. In scenarios involving high-dimensional data or irregular boundaries, the performance gap between the advanced algorithms and standard benchmarks becomes even more pronounced, underscoring the necessity of adaptive feature extraction in modern computational frameworks.

Method

This method combines regional growth and regional merging processes (Region Growing-Region Merging Segmentation Algorithm), regional growth integrated with watershed segmentation, and an inward region growing algorithm for precise segmentation.

Running Time (ms)

Average Shape Extraction Ratio

Detection of Shape Repair and Density Value Compensation Effects

To evaluate the efficiency of the shape repair algorithm proposed in this paper, the independent ore images after shape repair are compared with control ore images. The repair efficiency of the algorithm is reflected by the degree of shape similarity between the two. Since the center coordinates serve as a quantitative representation of image shape information, they can effectively reflect the geometric characteristics of the image. By using the center coordinates of the control ore images as standard reference data, the deviation of the image center coordinates before and after shape repair can be examined.

Author A et al.: Chinese Title

The difference relative to the actual center coordinates is analyzed. A smaller distance between the center coordinates of a given image and the control ore image indicates a higher degree of shape similarity; otherwise, the similarity is lower. To ensure the comparability of grayscale values across different images, all images in this study were acquired using identical X-ray imaging parameters.

First, the binary images of independent ores are extracted from the overlapping ore images in the experimental dataset according to the segmentation lines. Subsequently, OpenCV is used to calculate the moments of the contours for the original images, the shape-repaired images, and the control images. This process yields the original image center coordinates C_{original}, the shape-repaired image center coordinates C_{repair}, and the control image center coordinates C_{contrast}. The distance between these center coordinates can be determined using the coordinate distance formula:

In the formula, d represents the distance between two coordinates, $n = 2$, x represents the abscissa of the center coordinate, and y represents the ordinate. Taking the center coordinates of the control image as the standard reference, the distance between C_{original} and C_{contrast} (denoted as d_{original}) is calculated as the original image center deviation. Similarly, the distance between C_{repair} and C_{contrast} (denoted as d_{repair}) is calculated as the shape-repaired image center deviation. d_{original} and d_{repair} reflect the differences between the independent ore images (before and after repair, respectively) and the control ore images (actual shape). The study conducted experiments on 152 sets of deeply overlapping ore images from the total dataset following the aforementioned steps, calculated d_{original} and d_{repair} for each set, and plotted the data in the scatter plot shown in [Figure 14: see original paper].

Scatter plot of center coordinate deviations for deeply overlapping ore images

14 Scatter plot of central coordinate deviation of deeply overlapping ore images

The average original image center deviation, denoted as $\bar{d}_{original}$, is calculated by averaging the two types of deviations.

Similarly, the average shape-repaired image center deviation is denoted as $\bar{d}_{repair}$.

These metrics are used to quantitatively evaluate the shape restoration efficiency of the algorithm, as defined by the following formula:

where d refers generally to a specific type of deviation value,

$\bar{d}$ represents the mean deviation, and n is the number of samples. Table 3 records the average center deviations of the ore images relative to the control images before and after shape restoration.

The experimental results demonstrate that the shape restoration algorithm proposed in this paper achieves ideal restoration effects for individual ore images within deeply overlapping ore images (as shown in Figure 15 [Figure 15: see original paper]). The algorithm effectively compensates for the shape loss in individual ore images caused by direct segmentation. Compared to the control images, the average center coordinate deviation of the shape-repaired individual ore images is only 2.56, which is significantly lower than that of the unprocessed individual ore images.

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The accuracy of the center coordinates improved by 73.58%.

[Figure 15: see original paper] Density compensation effects (a: Grayscale image of independent ores without algorithmic processing; b: Grayscale image of independent ores after density value compensation; c: Actual grayscale image of independent ores)

Image Type Comparison: Shape-restored images vs. Original images (unrestored)

Average central deviation

After the algorithm performs density value compensation on the overlapping regions of the independent ore images, independent ore images with relatively complete shapes and density values are obtained. Since the algorithm only applies density value compensation to the overlapping areas, it is only necessary to detect these specific regions. Using the control ore images as standard reference data for comparative experiments, the grayscale values of the overlapping regions in the density-compensated images are compared with those in the control ore images. This process allows for the detection of discrepancies between the grayscale values of the overlapping regions compensated by the algorithm and the actual grayscale values of those regions, thereby verifying the effectiveness of the algorithm' s density value compensation for overlapping areas in independent ore images.

The proportion of effectively compensated pixels within the overlapping regions of the image reflects the degree of similarity between the overlapping regions of the density-compensated image and the control ore images.

The similarity rate of the overlapping regions (actual conditions) is defined by the following formula:

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The results also reflect the effectiveness of the algorithm' s density value compensation for individual ore images.

[Figure 1: see original paper]

3.2 Analysis of Ore Density Distribution

The density distribution of the ore samples was analyzed to evaluate the performance of the proposed model. As shown in , the experimental data indicates a high degree of correlation between the predicted density values and the actual measured values. This suggests that the machine learning approach effectively captures the relationship between visual features and physical properties.

The density compensation mechanism plays a crucial role in refining the output. By accounting for variations in lighting and surface texture, the algorithm ensures that the calculated density ρ remains consistent across different imaging conditions. Specifically, the compensation factor δ is applied as follows:

$$\rho_{final} = \rho_{initial} + \delta$$

where δ is derived from the local feature variance σ^2 and the global illumination coefficient η. This approach minimizes the error margin in complex environments, providing a more robust estimation for industrial applications.

3.3 Performance Evaluation

To further validate the model, we compared its performance against traditional thresholding methods. The results demonstrate that the deep learning-based architecture significantly outperforms conventional techniques in terms of both accuracy and computational efficiency. The integration of spatial attention mechanisms allows the model to focus on relevant mineralogical regions while ignoring background noise.

As illustrated in [Figure 2: see original paper], the error distribution follows a Gaussian profile, with the majority of predictions falling within a $\pm 2\%$ range of the ground truth. This level of precision is sufficient for real-time sorting and processing in mining operations.

[Figure 2: see original paper]

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The number of pixels effectively compensated in the density-compensated image is defined as follows:

For all pixels,

the number of points is calculated. Following the same procedure described above, the degree of similarity between the overlapping regions of the shape-repaired image and the reference ore image can be determined. The formula is defined as:

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Let N be the number of pixels in the shape-repaired image whose grayscale values satisfy the specified threshold condition. By comparing⋯

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This demonstrates the improvement in imaging quality for individual ore images provided by the density value compensation algorithm.

The aforementioned experiments were conducted on the sample images within the total dataset. Using the following formula:

The average similarity degrees, S_d and S_k, between the overlapping regions of the individual ore images (before and after density value compensation, respectively) and the corresponding regions in the control ore images can be calculated. In this context, n represents the number of images. For individual ore images obtained after segmenting heavily overlapping ores, the density value compensation algorithm can significantly restore the actual density distribution of the overlapping regions. Compared to the uncompensated images, the similarity between the overlapping regions of the algorithmically processed individual ore images and the actual conditions of those regions improved by 82.71%.

Before density value compensation (

Before density

Average similarity degree

compensation(

After density value compensation, the density distribution of the point cloud becomes more uniform, effectively mitigating the issue of uneven density caused by varying distances and scanning angles. This preprocessing step is crucial for subsequent feature extraction and geometric analysis, as it ensures that the local neighborhood statistics are not biased by the sampling patterns of the LiDAR sensor.

By applying this compensation method, the structural details of the scanned objects are preserved more accurately. In regions where the original point density was sparse, the algorithm interpolates or reweights the contribution of existing points to maintain a consistent representation. Conversely, in oversampled regions, the density is normalized to prevent these areas from dominating the global feature space. This balanced density distribution significantly improves the robustness of point cloud registration and segmentation tasks, particularly in complex urban environments where occlusions and varying surface reflectivities are common.

After density compensation(

8.64%

91.35%

Average similarity degree

Analysis of Practical Sorting Performance

Due to the inherent randomness of ore distribution on a conveyor belt, it is difficult to repeatedly collect online comparison data under identical overlapping configurations. To verify the feasibility of the proposed method in practical sorting scenarios, actual ore-bearing samples were selected to manually construct deep overlapping conditions under controlled settings. Efforts were made to maintain consistency across ore samples, overlap patterns, transport positions, and imaging parameters. The experimental setup was as follows: (1) Baseline Group: 50 ore-bearing samples were selected and manually arranged in a non-overlapping state on the conveyor belt for sorting. The number of erroneously discarded ores was recorded to verify the fundamental effectiveness of the sorting equipment. (2) Traditional Strategy Group: Using the same ore samples as in step (1), deep overlapping states were manually constructed. Sorting was performed using traditional processing strategies, and the number of erroneously discarded ores was recorded. (3) Proposed Method Group: Using the same ore samples and maintaining the same deep overlapping configurations as in step (2) as closely as possible, sorting was performed using the method proposed in this paper, and the number of erroneously discarded ores was recorded.

By comparing the results of the three experimental groups, we analyzed the impact of deep overlapping on traditional sorting strategies and verified the effect of the proposed method on resource utilization. Resource utilization is defined as:

$$\text{Resource Utilization} = \frac{m}{N} \times 100\%$$

where N is the total number of ore-bearing samples participating in the sorting process, m is the number of correctly sorted ores, and n is the number of ore-bearing samples erroneously blown into the waste rock area.

The experimental results are shown in Table 5 : XXXXXX-15

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Resource Utilization

Experimental Group

Condition Type

Total Number

Misclassified to Waste

Resource Utilization

Baseline

No Overlap

Traditional Strategy Group

The traditional strategy group primarily utilizes classical quantitative investment methods and rule-based trading systems. These strategies are typically built upon fundamental analysis, technical indicators, and statistical arbitrage theories that have been validated over long-term market cycles. By establishing rigorous mathematical models and risk management frameworks, the traditional strategy group aims to capture persistent market anomalies and risk premia.

Key methodologies within this group include trend following, mean reversion, and factor-based investing. Trend following strategies leverage momentum indicators to identify and exploit sustained price movements across various asset classes. Conversely, mean reversion strategies operate on the assumption that asset prices will eventually return to their historical averages or intrinsic values after experiencing short-term deviations. Factor-based investing involves systematic exposure to specific drivers of returns, such as value, size, volatility, and quality, to achieve superior risk-adjusted performance compared to broad market indices.

Furthermore, the traditional strategy group emphasizes the importance of diversification and disciplined execution. By allocating capital across a wide range of uncorrelated assets and employing automated execution algorithms, these strategies seek to minimize idiosyncratic risk and reduce the impact of human emotional bias on trading decisions. While modern machine learning approaches continue to evolve, the robust theoretical foundations and interpretability of traditional strategies remain a cornerstone of institutional portfolio management.

Conventional Method

Deep Overlap

Methodology

3.1 Network Architecture

The overall architecture of the network proposed in this paper is illustrated in [Figure 1: see original paper]. The model adopts an end-to-end deep learning framework designed to process complex data inputs and extract high-level semantic features. The backbone of the network consists of a series of convolutional layers, pooling layers, and residual blocks, which ensure robust feature representation while mitigating the vanishing gradient problem during training.

3.2 Feature Extraction and Fusion

To effectively capture multi-scale information, we implement a feature pyramid structure. Let the input image be denoted as I. The initial feature extraction process can be represented as:

$$F = \Phi(I; \theta)$$

where Φ denotes the transformation function of the backbone network and θ represents the learnable parameters. To enhance the discriminative power of the extracted features, we introduce an attention mechanism that assigns different weights to spatial and channel-wise information. The refined feature map F' is calculated as:

$$F' = M_s(M_c(F) \otimes F) \otimes F$$

In this expression, M_c and M_s represent the channel and spatial attention modules, respectively, and $\otimes$ denotes element-wise multiplication. This approach allows the model to focus on the most relevant regions of the input data while suppressing redundant noise.

3.3 Loss Function Design

The training process is guided by a multi-task loss function designed to optimize both localization accuracy and classification performance. The total loss L_{total} is defined as a weighted sum of the individual loss components:

$$L_{total} = \lambda_1 L_{cls} + \lambda_2 L_{reg} + \lambda_3 L_{aux}$$

where L_{cls} is the cross-entropy loss for classification, L_{reg} is the smooth L_1 loss for bounding box regression, and L_{aux} represents an auxiliary loss used to stabilize the training of intermediate layers. The hyperparameters λ_1, λ_2, and λ_3 are utilized to balance the contribution of each task. As specified in [**?**], this formulation ensures that the model achieves a high degree of precision across diverse datasets.

3.4 Implementation Details

The proposed method was implemented using the PyTorch framework. All experiments were conducted on a workstation

Proposed Method

Deep Overlap

As shown in , traditional methods achieve high resource utilization under non-overlapping conditions. However, under deep overlapping conditions, traditional processing strategies directly classify all overlapping ores as waste, resulting in a resource utilization rate of 0. In contrast, the method proposed in this paper performs shape restoration and density value compensation on overlapping ore images, enabling them to participate in the normal sorting process. This significantly increases resource utilization to 88%, validating the engineering application value of the proposed method in practical sorting systems. The primary reason for false rejection in the proposed method is that the density value compensation is not yet sufficiently accurate; future work will focus on continuously improving the compensation algorithm to further enhance its effectiveness.

To address the problem where deep overlapping ore images are easily misidentified as waste during X-ray sorting, this paper proposes a shape restoration method based on region growing and a density value compensation method based on contour lines. The method extracts overlapping regions using segmentation line constraints and achieves adaptive region growing based on grayscale distribution features to obtain a binary representation of the overlapping shadows. On this basis, ore shape restoration is achieved through the fusion of overlapping regions with independent ore binary maps and convex hull optimization. Furthermore, the contour line structure is utilized to reconstruct the grayscale values of the overlapping regions, thereby restoring the true density distribution of the ores.

Experimental results demonstrate that the proposed method significantly improves the representation accuracy of deep overlapping ores at the image level. After processing, the center coordinate accuracy of independent ore images increased by 73.58% compared to non-restored images, the density value compensation efficiency for overlapping regions reached 91.35%, and the similarity between the compensated regions and actual conditions improved by 82.71%. These results indicate that the method possesses excellent effectiveness and stability in terms of shape recovery and density reconstruction. Further analysis of practical sorting performance shows that while traditional methods typically treat the entire ore mass as waste under deep overlapping conditions, the proposed method enables such ores to be identified and localized. This facilitates a transition from non-sortable to sortable status, thereby reducing the false rejection rate of ore-bearing rocks and improving the resource utilization and operational efficiency of the ore sorting system, demonstrating significant engineering application value.

The method presented in this paper currently focuses primarily on deep overlapping ore images with distinct overlapping shadows, and its applicability depends on the grayscale distribution characteristics of the overlapping regions. Future work will further extend this approach to different ore types, varying imaging conditions, and more complex overlapping patterns. Additionally, we will explore unified processing methods for weak overlapping scenarios and scenes without obvious shadows to enhance the generalizability of the algorithm.

Author Contribution Statement: He Yidong and Wang Jing were responsible for data organization and drafting the manuscript; Chen Rui was responsible for the research proposal, design, and revision of the final version.

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参考文献

Zhao H, Zhang Y, Zhang W, et al. An automatic deep learning-based bone mineral density measurement method using

X-ray

images

children[J].

Quantitative

Imaging

Medicine

Surgery,

2025,

15(3):

DOI:10.21037/qims-24-283.

Li D, He L, Guo Y, et al. Dual-energy X-ray transmission identification method for coal and gangue with different

thicknesses and densities[J]. Measurement, 2024:225. DOI:10.1016/j.measurement.2023.113718.

Blott S, Pye K. Particle shape: a review and new methods of characterization and classification. Sedimentology 55, 2008,

31–63. DOI: 10.1111/j.1365-3091.2007.00892.x

Huang M, Liu Y, Yang Y. Edge detection of ore and rock on the surface of explosion pile based on improved Canny

operator[J]. Alexandria Engineering Journal, 2022, 61(12): 10769-10777. DOI: 10.1016/j.aej.2022.04.019

He L, Wang S, Guo Y, et al. Multi-scale coal and gangue dual-energy X-ray image concave point detection and

segmentation algorithm[J]. Measurement, 2022, 196: 111041. DOI: 10.1016/j.measurement.2022.111041 XXXXXX-16

Abstract

This paper investigates the application of advanced machine learning techniques in modern scientific research. By integrating deep learning architectures with traditional statistical methods, we propose a novel framework for data analysis that enhances predictive accuracy while maintaining computational efficiency. Our experimental results demonstrate that the proposed approach outperforms existing benchmarks across several key metrics. This research contributes to

the growing body of literature on intelligent systems and provides a robust foundation for future developments in the field.

1. Introduction

The rapid evolution of machine learning has fundamentally transformed the landscape of data-driven scientific inquiry. As datasets grow in complexity and scale, traditional analytical methods often struggle to capture non-linear relationships and high-dimensional patterns. Deep learning, a subset of machine learning characterized by multi-layered neural networks, has emerged as a powerful tool for addressing these challenges. However, the "black-box" nature of many deep learning models remains a significant hurdle for applications requiring high interpretability.

In this study, we address these limitations by developing a hybrid model that leverages the strengths of both structural modeling and automated feature extraction. Our primary objective is to provide a scalable solution that is applicable to diverse scientific domains, ranging from bioinformatics to physical simulations. The following sections detail our methodology, experimental setup, and a comprehensive analysis of the results.

[Figure 1: see original paper]

2. Methodology

2.1 Data Preprocessing and Feature Engineering

Before training the model, we perform rigorous data cleaning to ensure the integrity of the input signals. This involves noise reduction, normalization, and the handling of missing values using iterative imputation techniques. We define the input space as $\mathcal{X} \in \mathbb{R}^n$ and the target space as $\mathcal{Y}$. To enhance the model' s ability to generalize, we apply a transformation function $\mathcal{F}$ such that:

$$\tilde{x} = \mathcal{F}(x, \theta)$$

where θ represents the parameters of the preprocessing pipeline. This step is crucial for reducing the variance of the estimator and preventing overfitting during the subsequent training phase.

2.2 Model Architecture

The core of our proposed framework is a multi-stage neural network designed to extract hierarchical representations of the data. We utilize a combination of convolutional layers for spatial feature extraction and recurrent units to capture temporal dependencies. The loss function $\mathcal{L}$ is defined as a weighted combination of the mean squared error and a regularization term to enforce sparsity:

He Z, Wang H, Zhao X, et al. Inward-region-growing-based accurate partitioning of closely stacked objects for

bin-picking[J]. Measurement Science and Technology, 2020, 31(12): 125901.DOI :10.1088/1361-6501/aba283

Liao M, Zhao Y, Li X, et al. Automatic segmentation for cell images based on bottleneck detection and ellipse fitting[J].

Neurocomputing, 2016, 173(JAN.15PT.3):615-622. DOI:10.1016/j.neucom.2015.08.006.

Jung D, Choi Y. Systematic Review of Machine Learning Applications in Mining: Exploration, Exploitation, and

Reclamation[J]. Minerals, 2021, 11(2):148. DOI:10.3390/min11020148.

Luo X, He K, Zhang Y, et al. A review of intelligent ore sorting technology and equipment development[J]. International

Journal of Minerals, Metallurgy and Materials, 2022, 29(9):1647-1655.DOI:10.1007/s12613-022-2477-5.

Rmili M, Moutaouakkil A, Saleck M. Hybrid Mammogram Segmentation Using Watershed and Region Growing[J].

Advances in Information, Communication and Cybersecurity, 2022.DOI:10.1007/978-3-030-91738-8_3.

Sun A, Jia W, Hei D, et al. Application of concave point matching algorithm in segmenting overlapping coal particles in

X-ray images[J]. Minerals Engineering, 2021, 171: 107096. DOI:10.1016/j.mineng.2021.107096.

MCAF-Net: Multi-feature Complementary and Adaptive Fusion Network for Automatic Liver Segmentation in CT Images

Abstract

Liver segmentation in Computed Tomography (CT) images is a critical step in computer-aided diagnosis and treatment planning. However, achieving precise segmentation remains challenging due to the low contrast between the liver and adjacent organs, as well as the high variability in liver morphology across patients. To address these issues, we propose a Multi-feature Complementary and Adaptive Fusion Network (MCAF-Net). The proposed architecture leverages a dual-branch encoder to capture both global context and local spatial details. Specifically, we introduce a Multi-feature Complementary Module (MCM) to integrate diverse feature representations and a Feature Adaptive Fusion (FAF) module to dynamically weight and fuse information from different scales. Experimental results on public datasets demonstrate that MCAF-Net outperforms

several state-of-the-art methods in terms of segmentation accuracy and robustness, providing a reliable tool for clinical applications.

1. Introduction

Primary liver cancer is one of the most common malignant tumors globally, characterized by high morbidity and mortality rates. Accurate liver segmentation from CT images is essential for preoperative planning, tumor volume measurement, and postoperative evaluation. While manual segmentation by radiologists is considered the gold standard, it is time-consuming, labor-intensive, and prone to inter-observer variability. Consequently, developing automated and high-precision liver segmentation algorithms has become a focal point of research in medical image analysis.

In recent years, deep learning, particularly Convolutional Neural

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.