Feature Analysis and Target Detection of High-resolution Remote Sensing Image of Coal Mining Subsidence Area

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Abstract. Aiming at the phenomenon of regional ground collapse caused by mining, the site information is obtained through field investigation, and the features of typical collapse targets are described. The drone remote sensing images are used to extract and analyze the color features and shape features of typical collapse targets. Combine the Hough transform, shadow and Harris corner detection methods to achieve the target detection of collapsed pits and trough collapsed areas. The combined method uses Hough transform to detect the edge shape curve of the collapsed pits and trough collapsed areas, and use shadow detection method to extract its internal areas, and Harris corner detection method is used to locate local feature points in the image. Experimental analysis results show that the method has good application effect on target detection in collapsed pits and trough collapsed areas.

1. Introduction
Coal mining is a complex process. In this process, it is easy to cause different types of ground disasters such as ground subsidence, ground collapse, landslide, collapse, and ground fissures. The mining of the mine makes the residential area, structures, water and land resources, land Resources are affected by varying degrees, and this process severely restricts the ecological environment and sustainable development of the mining area [1]. In recent years, the rapid development of high-resolution ground observation technology has played an important role in monitoring and evaluation of land use, environment and geological disasters in mining areas. The research on information extraction in coal mining subsidence areas can be divided into three Aspects: ①Survey of ground subsidence disasters in the surface subsidence area of the mine [2-3]; ②We deeply analyze the remote sensing image characteristics of different types of geological hazards or typical features in the subsidence area of the coal mining subsidence area, this method more accurately determines the subsidence area The location or the automatic extraction of typical features in the subsidence area [4-6]; ③ This method is fused with multi-source multi-point time-phase remote sensing image data, and the technology has mastered the spatial and temporal distribution law of goaf collapse [7-8]. However, the remote sensing image characteristics and target detection of typical collapse targets in coal mining subsidence areas still need further study.

In this paper, a subsidence area of a mining area in northern Shanxi Province was selected as the test area. We obtained field information through field investigations to describe the characteristics of typical subsidence targets. Using UAV remote sensing images, we performed color characteristics and
shapes of typical coal mining subsidence targets. Feature extraction and analysis. In this study, Hough transform, shadow and Harris corner detection methods are combined to achieve target detection of coal mining collapse pits and trough-shaped collapse areas.

2. Characteristic analysis of typical targets in coal mining subsidence area
In this paper, the subsidence area of a mining area in northern Shanxi Province is selected as the test area. The coal mining subsidence area belongs to the typical low mountain hilly landform. The overall vegetation coverage of the coal subsidence area is low. The original terrain is approximately stepped. The UAV remote sensing images of the subsidence area can be seen that the surface of the subsidence area is mostly large grassland and fragmented sporadic natural forest land (as shown in Figure 1).

![Image of the study area](image1.jpg)

**Figure 1.** UAV remote sensing image of the study area

2.1. Characterization
We have found through field investigations that we found that the surface collapse in the coal mining subsidence area is mainly represented by large stepped graben-like ground fissures and a few existing collapse pits, as well as the concentrated distribution of collapse in the gully area.

2.1.1. Ground fissures in coal mining subsidence area. The ground fissures in the coal mining subsidence area are linear, curved, broken or irregular, with one or more parallel and irregular arrangements. The topographic difference between the two sides of the ground fissure is obvious or no obvious change (see Figure 2(a)). The long-short or long worm-shaped or broken line shape on the UAV remote sensing image, and multiple ground fissures are arranged in cross, parallel or irregular; the color of these areas is black or gray-black (as shown in Figure 2(b)).

![Image of ground fissures](image2.jpg)

**Figure 2.** Graben collapse
2.1.2. Trough collapse in coal mining subsidence area. The trough-shaped collapses in coal mining subsidence areas are generally elongated and continuous or intermittently distributed on the ground surface of the subsidence area, and their extension direction is consistent with the coal seam. This trough-shaped collapse is similar to the graben, with cracks on both sides. The bottom of the trough-shaped collapse is flat, and the collapse boundaries on both sides are generally neat (as shown in Figure 3(a)). The images of these areas appear as obvious strip-shaped collapsed areas on the UAV remote sensing image, and the intermediate collapsed area may not be significantly different from the surrounding tones; the collapsed area below us will form a long and low drop due to surface collapse, which will form a long striped shadow area (as shown in Figure 3(b)).

![Figure 3. Trough collapse](image)

2.1.3. Collapse pits in coal mining subsidence area. The pits in the coal mining subsidence area are cylindrical or funnel shaped, and most of the pit walls are steep and distributed in groups (as shown in Figure 4(a)). On the remote sensing image of the UAV, there are circular or elliptical patterns with clear boundaries. The collapsed pits with a smaller area are darker in color due to the effect of shadows (as shown in Figure 4(b)); we find that the internal tones with larger areas are different in light and dark tones, and are often found in the lower half of the inside of the oval pattern. Heavy shadows appear (as shown in Figure 4(c)).

![Figure 4. Collapse pits](image)

2.1.4. Collapse of coal mining subsidence area. The back wall of the collapsed collapsing body in the coal mining subsidence area is relatively smooth, and there are a large number of accumulation bodies at the front end, which destroys the original topography and landform, and generates a large amount of bare soil to reduce the vegetation coverage in this area (as shown in Figure 5(a)). On the UAV remote sensing images, the shape is generally long, tongue-shaped or fan-shaped, etc.; we found that the trailing edge of the collapsed body in this area is generally curved or irregularly curved steep terrain, and the accumulation body at the front end is basically not covered by vegetation. The features are obvious; the color difference between the collapsed body and its surrounding area is large, the internal texture is rough, and the color tone is mostly gray. The sun-slope area is generally light-toned, and the shady-slope area is heavily shaded. (As shown in Figure 5(b)).
2.2. Characteristic analysis of coal mining subsidence area

In this paper, the remote sensing image samples of ground fissures, trough collapses, collapse pits and collapses in the collapse area are selected, and their rough boundaries are artificially delineated, and then the analysis of color and shape characteristics is performed. The selected image samples are shown in Figure 6. Show. Fig. 6(c) is a collapse pit with a small area, and Fig. 6(d) is a collapse pit with a large area.

![Image samples of ground collapse](image)

(a) Grain collapse  (b) Trough collapse  (c) Collapse pit 1  (d) Collapse pit 2  (e) Collapse

**Figure 6.** Image samples of ground collapse

2.2.1. The color characteristics analysis of coal mining subsidence area. The color feature extraction of the coal mining subsidence area was carried out with the help of ENVI remote sensing image processing software. The color features we extracted included the minimum, maximum, average and standard deviation of each band. The results are shown in Table 1.

| Statistics          | Grain collapse | Trough collapse | Collapse pit 1 | Collapse pit 2 | Collapse |
|---------------------|----------------|-----------------|----------------|----------------|----------|
| Minimum value       | 31.67          | 37.33           | 26.33          | 21.67          | 34.67    |
| Maximum             | 99.33          | 201.67          | 140.67         | 211            | 215.67   |
| Mean                | 56.95          | 126.67          | 48.03          | 121.00         | 153.51   |
| Standard deviation  | 11.13          | 37.60           | 20.80          | 44.51          | 36.86    |

The ground fissures in the coal mining subsidence area and the smaller area of the subsidence pits all appear as the same dark features on the image, and their color characteristics are mainly manifested as the maximum value, mean value and standard deviation are much smaller than other types of subsidence.

Trough-shaped collapses and large-area collapse pits are mixed areas of shadows and bare soil. Their color characteristics mainly show large values but relatively small collapses. The mean and standard deviation are much larger than ground fissures and small-area collapse pits.
Collapse. Because the entire collapse body is located on the sunny side, the overall brightness value is large, so the color characteristics of collapse mainly show that the maximum value and the average value are larger than other types of collapse.

2.2.2. Analysis of shape characteristics of coal mining subsidence area. The shape feature extraction of the coal mining subsidence area in this experiment is assisted by ENVI remote sensing image processing software, and the minimum circumscribed rectangle required to calculate the shape feature is manually delineated in the sample image. The shape features we extracted include aspect ratio, compactness, rectangularity and shape index. The calculated shape characteristics are shown in Table 2.

| Statistics     | Grain collapse | Trough collapse | Collapse pit 1 | Collapse pit 2 | Collapse |
|----------------|----------------|-----------------|----------------|----------------|----------|
| Aspect ratio   | 10.15          | 5.10            | 1.24           | 2.04           | 1.41     |
| Compactness    | 221.00         | 30.79           | 11.50          | 15.60          | 14.11    |
| Rectangularity | 0.05           | 0.81            | 0.65           | 0.71           | 0.93     |
| Shape index    | 3.72           | 1.39            | 0.85           | 0.99           | 0.94     |

The aspect ratio of coal mining subsidence area is used to distinguish slender targets from circular or square targets. The linear ground fissures have the largest aspect ratio, and the approximate circular collapse pit 1 has the smallest aspect ratio. The order of the aspect ratio of other collapse types is: trough collapse (5.10)>collapse pit 2 (2.04)>collapse (1.41).

The compactness of the coal mining subsidence area indicates the similarity between the shape and the circle. The compactness value of the circle is 4π. The larger the value, the smaller the similarity to the circle. Collapse pit 1 has the smallest compactness value and is closest to a circle. The order of compactness of other types of collapses is: ground fissure (221.00)>trough collapse (30.79)>collapse pit (15.60)>collapse (14.11).

The squareness of the coal mining subsidence area reflects the degree of fullness of the area to its circumscribed rectangle. The value ranges from 0 to 1. The thinner and more curved the ground feature, the smaller the squareness. We found that the collapse of the elongated groove and the collapse of the approximately rectangular shape have the highest similarity to the rectangular shape, the value of the rectangularity is also large, and the elongated curved ground fissures have the smallest rectangularity.

The shape index of the coal mining subsidence area is used to describe the smoothness of the area boundary. The more broken the area object, the larger the shape index. We rank the shape index as follows: ground fissure type (3.72)>groove collapse type (1.39)>collapse pit 2 type (0.99)>collapse type (0.94)>collapse pit type 1 (0.85).

3. Remote sensing image target detection method
Different collapsing targets in coal mining subsidence area show different color and shape features on the UAV remote sensing image. The collapse pits with a smaller area have the highest similarity to a circle; those with a larger area approximate to an ellipse; the linear characteristics of ground fissures are obvious; and the trough-shaped collapses are elongated. Therefore, the Hough Transform (Hough Transform) method is used to detect the shape of the edge curve of different collapsed targets, and then combined with other methods such as shadow detection to extract the internal area of the collapsed area to achieve the detection of typical collapsed targets.

3.1. Harris corner detection
The corner points of the coal mining subsidence area are distributed in large numbers on man-made objects, which are local feature points that are easy to locate in the image [9]. Harris corner detection steps are: 1. Use the difference operator to calculate the gradient and square of each pixel in the X and
Y directions of the image; 2. Use the Gaussian filter to remove the noise points from the previous step; 3. Calculate the image interest value of each corresponding point in the region, and local non-maximum suppression in the rectangular neighborhood; 4. Set a threshold, if the interest value of the point is greater than this threshold and is a local maximum in a certain area, then this point is considered to be a corner point.

3.2. Hough transform

The core idea of Hough Transform is to transform the parameter space and use a voting mechanism to detect objects with specific shapes. The Hough transform was first proposed by Paul Hough in 1962 [10]. The classic Hough transform is the Hough line detection. Later, the Hough transform was extended to detect objects such as circles and ellipses. The generalized Hough transform proposed by Ballard [11] effectively solves the problem of detecting arbitrary shapes.

The shape of a model can be defined by the curve of the following formula (1):

$$v(\theta) = x(\theta) \begin{bmatrix} 1 \\ 0 \end{bmatrix} + y(\theta) \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Formula (1)

$$\omega(\theta) = (\theta, b, \lambda, \rho) = b + \lambda R(\rho)v(\theta)$$

In the formula, it is a translation vector, $\lambda$ is a scale factor, and is a rotation matrix. The shape depends on four parameters: two parameters define the position $b$, plus rotation and scale.

The generalized Hough transform is not to find a general parameter equation that can represent any shape, but to express a shape in the form of a table, storing all edge points and their directions in the graph in a table, which is equivalent to the The shape of the graph is determined. Therefore, whether it is a straight line, a circle, an ellipse or other geometric shapes, you can use this method to detect.

In general, if we want to perform a generalized Hough transform, we must first construct an R table to describe the shape of the template. First select a reference point (you can select any point on the image), and then calculate the vector $(r, \beta)$ of each edge point on the template image pointing to the reference point. The geometric relationship between the edge point and the reference point is shown in Figure 7. As shown, $a$ represents the position of the selected reference point, $x$ represents any edge on the edge of the image, $r$ represents the length from the boundary point to the selected reference point, and $\beta$ represents the angle between the line from the reference point to the boundary point and the tangent of the boundary point. Then this paper calculates the gradient direction $\theta$ of the edge point of the template image. We discretize the calculated gradient direction into $N$ (generally 30) intervals, and use this as an index to store the corresponding vector $(r, \beta)$ in the R table. Get R form see table 3. Finally, the target image is detected. First, an accumulation space is established. We substitute each edge point in the target image into the R table to obtain all r values. We vote on the reference point corresponding to each r value in the accumulation space. Vote The position of the accumulated space with the higher value is the position of the optimal reference point of the target shape, so that certain specific shapes on the target image are detected.

In the formula, the model shape curve is expressed, and for a circle, the sum is satisfied. Arbitrary shapes can be expressed by following a more complex definition. By considering translation, rotation and scale changes, the shape of the image can be defined as the following formula (2):
Figure 7. Relationship between edge points and reference points

Table 3. R table structure

| i  | $\theta_i$ | $(r, \beta)$  |
|----|------------|----------------|
| 0  | 0          | $(r_0, \beta_0), (r_1, \beta_1), (r_2, \beta_2), \ldots$ |
| 1  | $\Delta \theta$ | ... |
| 2  | $2\Delta \theta$ | ... |
| ... | ...       | ... |

3.3. Shadow detection

Remote sensing image shadow detection is mainly divided into two categories: detection methods based on shadow properties and model-based detection methods [13]. Studies have shown that the HIS color space is the closest to the human cognition color space, and can best reflect the way the human visual system perceives color [14]. The conversion formula from RGB color space to HIS color space is shown in equations (3)-(6).

$$I = \frac{1}{3} (R + G + B)$$

$$S = 1 - \frac{3}{R + G + B} \min (R + G = B)$$

$$H = \begin{cases} \theta (B \leq G) \\ 360 - \theta (B > G) \end{cases}$$

$$\theta = \arccos \frac{(R - G) + (R - B)}{2\sqrt{(R - G)^2 + (R - B)(G - B)}}$$

In the HIS color space, the characteristics of the shadow area are mainly as follows: the brightness value is low, that is, the I value is small; the saturation is high, that is, the S value is large; the hue value is large, that is, the H value is large. The methods of using the HIS model for shadow detection mainly include the difference method (SI), the ratio method (S/I), the normalized difference method ((SI)/(S+I)) and Yang Jun et al. [15]. Tsai’s ((H+1)/(I+1)) [16].
Select the ratio method (S/I) to detect the shadow of the collapsed area, the specific steps are as follows:

1. Calculate the ratio of the S channel and the I channel of the HIS color space, and after obtaining the ratio image, automatically determine the threshold according to the Otsu method and detect the preliminary shadow area;
2. Calculate the histogram of the green G channel in the RGB color space for the shadow area of the shadow detection result in step 1, and also use the Otsu method to automatically determine the threshold value and binarize it to obtain the candidate area of the shadow area;
3. Since the shadow area also has a high saturation feature, the Otsu method is used to automatically divide the saturation component of the candidate area in step 2 and then perform morphological operations on the resulting binary image. Remove smaller patches to get the final shadow detection result.

4. Detection and analysis of typical targets in subsidence area

4.1. Detection of collapse pits

The smaller area of the collapse pit is similar to a circle on the UAV remote sensing image, and the entire interior appears as a dark shaded area due to the shadow. Therefore, first, the edge shape of the collapsed pit with a small area is detected by the Hough circle detection method, and then the shadow area inside the collapsed pit is extracted, and finally the detection of the collapsed pit is realized.

The large-area collapse pits appear on the UAV remote sensing image as an approximate ellipse shape. The internal tones of the collapse pits have different light and dark shades. In the lower half of the inside of the ellipse pattern, there are often heavy shadows, and the upper side is bright. Bare soil area. The parameter space dimension of Hough ellipse detection is high, and the calculation speed is slow. Therefore, the generalized Hough transform method is used to detect the edge shape of the large-scale collapse pit, and then the shadow area inside the collapse pit is extracted, and then using the Otsu method automatic threshold segmentation to extract the bright bare soil area inside the collapsed pit, and finally realize the detection of the collapsed pit.

4.1.1. Collapse pit corner detection. In this paper, Harris corner detection is carried out on the collapsed pit. The detection results are shown in Figure 8. It can be seen that the edge of the collapse pit caused by the ground collapse is not as neat as the artificial building, so a large number of corner points will be generated at its edge. The large-area collapse pits are internally chaotic. The detected corners are mainly distributed at the edges and internal areas of the collapse pits. The more chaotic the interior of the collapse pits, the denser the detected corners.

4.1.2. Edge shape detection of collapse pit. Hough circle detection is the process of converting a circle in the two-dimensional image space into a point in the three-dimensional parameter space.
determined by the radius and the horizontal and vertical coordinates of the center of the circle. The gradient is usually used to convert the three-dimensional parameter space into two dimensions. The principle of the gradient method is that the modulo vector of each point on the circle (the vertical line of the tangent of the point on the circle) points to the center of the circle, and the intersection of the modulo vectors of the points on the circle is the center of the circle. The first step of the gradient method is to find these centers; then the radius is determined according to the number of votes of all non-zero points on the edges of the centers.

The detection result of the edge shape of the collapsed pit with a small area is shown in FIG. 9. It can be seen that the position and approximate edge shape of the collapsed pit are well detected.

The detection of the shape of the collapsed pit based on the generalized Hough transform must first perform edge detection, and then construct the edge curve template of the collapsed pit, and finally realize the detection of the shape of the collapsed pit.

1. Edge detection

Canny edge detection can obtain the optimal edge detection effect by adjusting the appropriate high and low thresholds. Compared with the hand-drawn edge map (Figure 6(d)), two thresholds with different heights are set to select the optimal threshold. The final optimal threshold is 0.1 and 0.6. The edge detection results are shown in Figure 10(a).

2. Model building

According to the edge detection result, the ellipse closest to the edge shape of the collapse pit is selected as the template, and the selected template shape is shown in FIG. 10(b). Then set the position of the template reference point at the upper left corner (1,1) of the image, calculate the vector r of all the edge points and reference points in the edge image, and store it in the R table to construct the detection model.
(3) Edge shape detection

In this paper, the detection model constructed by the above steps is used to detect the target image. The accumulation space is first established. Each edge point in the target image is substituted into the R table to obtain all r values. The reference point corresponding to each r value is in the accumulation space. In the voting, the cumulative space position with the higher voting value is the position of the best reference point of the target shape, so that the specific shape on the target image is detected.

The Hough accumulation space generated during the detection of collapse pits is shown in Fig. 11(a). The position of the maximum value (the brightest point in the figure) in the Hough accumulation space is the position of the reference point. As shown in the final test result 11(b), it can be seen that the position and approximate edge shape of the collapse pit are well detected.

![Hough space](image1)

(a) Hough space

![Test results](image2)

(b) Test results

**Figure 11.** Hough space and detection result image

4.1.3. Internal area detection of collapse pit. The Hough circle detection method has detected the location and approximate edge shape of small collapse pits, and then uses shadow detection to extract its internal area. The extraction results are shown in Figure 12. Finally, the detection of the collapse pit with a small area is realized.

![Image of detection results of collapse pit](image3)

**Figure 12.** Image of detection results of collapse pit

The generalized Hough transform detects the location and approximate shape of a large-scale collapse pit, and then performs shadow detection on the collapse pit to extract the shadow area inside the collapse pit. The result is shown in FIG. 13(a); the Otsu method is used to automatically Threshold segmentation extracts the bright-colored bare soil area inside the collapse pit, and the result is shown in Fig. 13(b). Finally, the detection of collapse pits is achieved, and the detection results are shown in Figure 13(c).
4.2. Detection of trough collapse area
The trough-shaped collapsed area appears as a long strip on the UAV remote sensing image. The internal composition is similar to the larger area of the collapsed pit. The internal tone is different in light and dark. There are often heavy shadows in the lower half of the inner side of the hand-shaped figure. On the upper side is a bare earth area with bright tones. Therefore, the generalized Hough transform method is used to detect the edge curve segments of the trough-shaped collapsed area, and then the shadow area inside the collapsed area is extracted, and then the Otsu method is used to automatically threshold to extract the bright bare soil area inside the collapsed area. Detection of trough-shaped collapse area.

4.2.1. Harris corner detection. The corner points detected by the trough collapse are scattered in the trough collapse area except for the points scattered in the collapse area. Due to the irregular shape of the trough collapse border, the internal tone is different from the light and dark. The corner points are mainly concentrated on the boundary of the shaded area under the trough-shaped collapse (as shown in Figure 14).

4.2.2. Detection of edge curve of trough collapse area. (1) Edge detection
In this paper, two thresholds with different high and low thresholds are set to select the optimal threshold. The final optimal threshold is 0.1 and 0.8. The edge detection results are shown in Figure 15(a).

(2) Model building
Based on the edge detection results, we select edge shape curve segments on both sides of the trough-shaped collapse area as detection templates (as shown in Figure 15(b)). The edge curves on
both sides of the trough-shaped collapse are the main components of the trough-shaped collapse. The extension direction and width variation of the trough-shaped collapse are all reflected in the characteristics of the edge curve. Similarly, set the position of the reference point at the upper left corner of the image (1,1) as the template, calculate the vector r of all the edge points and reference points in the edge image, and store it in the R table to build the detection model.

![Edge detection results](image1.png) ![Detection template](image2.png)

**Figure 15.** Edge detection results and detection template

(3) Edge curve detection
We use the detection model constructed in the above steps to detect the target image, and also establish an accumulation space. Substitute each edge point in the target image into the R table to obtain all r values. For each r value, the reference point corresponds to the accumulation space. The voting is performed in the middle, and the position of the accumulated space with the higher voting value is the position of the best reference point of the target shape.

The Hough accumulation space generated during the detection of the trough-shaped collapse area is shown in Fig. 16(a). The position of the maximum value (the brightest point in the figure) in the Hough accumulation space is the position of the reference point. The final edge curve detection result is shown in 16(b).

![Hough space](image3.png) ![Test results](image4.png)

**Figure 16.** Hough space and detection result image

4.3. Detection of the internal area of the trough-shaped collapse area
The generalized Hough transform detects the edge curve of the trough-shaped collapsed area, and then performs shadow detection on the trough-shaped collapsed area to extract the internal shadow area. The result is shown in Figure 17(a); then, the Otsu method is used to automatically extract the threshold segmentation. The bright-colored bare soil area inside the trough-shaped collapse area is
shown in Figure 17(b). Finally, the detection of collapse pits is achieved, and the detection results are shown in Figure 17(c).

![Shadow detection result](image1)
![Bare soil test results](image2)
![Identification result of collapse pit](image3)

**Figure 17.** Detection results of the trough collapse area

5. Conclusion
Different subsidence targets in the coal mining subsidence area show different color and shape features on the UAV remote sensing image. In this paper, we obtain the on-site information of the collapsed area through field investigation. We describe the characteristics of typical collapsed targets and extract and analyze the color and shape features of the typical collapsed targets on the UAV remote sensing image. Then we use Hough transform, shadow and The combined method of Harris corner detection finally realizes the target detection of collapsed pits and trough-shaped collapsed areas. We found that this method uses Hough transform to detect the edge shape curve of collapsed pits and trough-shaped collapsed areas. This method uses shadows The detection method extracts its internal area, and we use the Harris corner detection method to locate local feature points in the image. The results show that the method has good application effect on target detection in collapsed pits and trough-shaped collapsed areas.

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