Article

The Surface Crack Extraction Method Based on Machine Learning of Image and Quantitative Feature Information Acquisition Method

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Abstract: In order to effectively control the damage caused by surface cracks to a geological environment, we need to find a convenient, efficient, and accurate method to obtain crack information. The existing crack extraction methods based on unmanned air vehicle (UAV) images inevitably have some erroneous pixels because of the complexity of background information. At the same time, there are few researches on crack feature information. In view of this, this article proposes a surface crack extraction method based on machine learning of UAV images, the data preprocessing steps, and the content and calculation methods for crack feature information: length, width, direction, location, fractal dimension, number, crack rate, and dispersion rate. The results show that the method in this article can effectively avoid the interference by vegetation and soil crust. By introducing the concept of dispersion rate, the method combining crack rate and dispersion rate can describe the distribution characteristics of regional cracks more clearly. Compared to field survey data, the calculation result of the crack feature information in this article is close to the true value, which proves that this is a reliable method for obtaining quantitative crack feature information.

Keywords: machine learning; remote sensing; UAV image; crack extraction; feature acquisition

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1. Introduction

In western China, especially in arid and semiarid areas, surface cracks are caused by human activities, such as coal mining [1], soil erosion, building damage, vegetation withering, and other geological environment problems caused by surface cracks [2–4]. In order to effectively control the damage caused by surface cracks to a geological environment, we need to find a convenient, efficient, and accurate method to obtain crack information, which can be used to study the development regularity of surface cracks and to evaluate the risk in providing guarantees for land reclamation [5].

At present, the methods of crack extraction mainly include field surveys, radar detection technology [6,7], satellite remote sensing imaging [8], and unmanned air vehicle (UAV) imaging [9]. Field surveys are expensive and inconvenient [10]. Radar technology is successfully used in landslide monitoring and surface crack detection [11]. However, due to the complex geological environment in arid and semiarid areas, the ground surface has large fluctuations and the distribution of soil crusts and vegetation is disorderly. Thus, the conditions required to use radar to detect ground cracks are limited. Satellite remote sensing imaging is a method used to extract cracks from images, but the accuracy is low. In contrast, UAVs have obvious advantages, such as high efficiency, flexible maneuverability,

high resolution, and low operating costs. Their resolution can reach the level of centimeters [12], which provides an ideal data source for information extraction of surface cracks. At present, the methods for extracting surface cracks from UAV image data are mainly edge detection [13], threshold segmentation [14], supervised classification [15], and manual artificial visual interpretation [10]. At the same time, there are also scholars applying machine learning techniques to crack extraction methods in roads and buildings [16,17].

The existing crack extraction methods based on unmanned air vehicle (UAV) images inevitably have some erroneous pixels because of the complexity of background information [9], which interfere with the subsequent calculation and analysis of crack feature information, and cannot provide accurate data support to study the development of surface cracks and to assess the risk. At the same time, most of the current research focuses on the surface crack extraction of UAV images, and there are few researches on the calculation methods for crack feature information. The content, calculation method, and image preprocessing steps of crack feature information have not been systematically clarified.

In view of this, this article proposes a surface crack extraction method based on machine learning of UAV images; the data preprocessing steps; the contents from crack feature information, including length, width, direction, location, fractal dimension, number of cracks, crack rate (area density), and dispersion rate; and the calculation methods for these crack feature information. The reliability of the method is evaluated by a comparison with field survey data.

The rest of this article is organized as follows. Section 2 introduces the materials and methods. Section 3 shows the results and discusses. The final section summarizes the research conclusions.

2. Materials and Methods

2.1. Data Source and Research Methods

2.1.1. Data Source

The research object was surface cracks from UAV images in arid and semiarid areas, and the research area was located in Yulin, Shaanxi Province, China. An example of unmanned aerial vehicle (UAV) image data is shown in Figure 1. The parameter information of the UAV image data is shown in Table 1.

Figure 1. The UAV image synthesized through the RGB band.

Table 1. UAV image data parameter information.

Parameters	Value
Data type	Multispectral image
Flight date	27 June 2019
Flight height	25 m
UAV model	M210RTK
Camera model	MS600pro
Focal length	6 mm
Band range	450 nm, 555 nm, 660 nm, 710 nm, 840 nm, and 940 nm
Ground spatial resolution (GSD)	1.5 cm

2.1.2. Research Methods

This article proposes a surface crack extraction method based on machine learning of UAV images and the quantitative feature information acquisition method. A flowchart is shown in Figure 2. First, cracks are extracted from UAV images based on machine learning, then the crack extraction image is preprocess, and finally the feature information from the cracks is obtained. Specific descriptions of the method are described in subsequent sections.

Figure 2. Flowchart of the crack extraction and feature information acquisition methods for a UAV image.

2.2. Crack Extraction Method Based on Machine Learning

2.2.1. Dataset Construction and Crack Extraction Steps

Crack extraction using UAV images is a high-resolution, flexible-maneuverability, high-efficiency, and low-operating-cost method. However, the existing crack extraction methods based on UAV images inevitably have some erroneous pixels because of the complexity of background information. Though image cutting to reduce the complexity of the background information of an UAV image and then extracting crack image and re-splicing proved to be a reliable method of crack extraction [9], after image cutting, the number of images increases. It is reasonable to extract cracks only from the sub-images containing cracks. Therefore, the sub-images are divided into two categories through machine learning: cracks and no cracks; the steps in the method are shown in Figure 2.

First, a UAV image is cut into 50×50 pixel sub-images. Second, datasets are constructed based on different background information from the sub-image: bare ground, soil crusts, and green vegetation. Third, with cracks and no cracks as labels and RGB three-band values as features, 400 images are selected for each dataset to establish training samples. Fourth, using the machine learning method of support vector machine (SVM) [18] and the dimensionality reduction method of F-Score feature selection [19], the sub-images in each dataset are divided into two categories, cracks and no cracks, and the leave-one-out cross-validation and permutation test are used for accuracy verification [20]. Fifth, cracks from sub-images with cracks are extracted and sub-images without cracks are backgrounded. Sixth, the processed sub-images are re-spliced to obtain the results of an UAV image crack extraction. Figure 3 shows the classification results and crack extraction results of each dataset.

Figure 3. Classification results of each dataset, crack extraction, and background processing results.

It needs to be specifically explained that, when constructing the datasets of sub-images, 10% is taken as the threshold. When the proportion of soil crusts in a sub-image is greater than 10%, it is classified as a soil crust dataset. When the proportion of green vegetation is greater than 10%, it is classified as a green vegetation dataset. When the soil crusts and green vegetation are both greater than 10%, it is classified as a dataset of higher proportion. The remaining sub-images are classified as bare field datasets.

SVM is a two-class classification model. Its basic model is a linear classifier that searches for separation hyperplanes with a maximal interval in the feature space. V-SVM is chosen as the algorithm model in this study [21]. In the case of linear separability, the V-SVM model is as follows [9]:

$$\min = \frac{1}{2} \|w\|^2 - \rho v + \frac{1}{l} \sum_{i=1}^l \xi_i \quad (1)$$

$$s.t. y_i [w^T x_i + b] \geq \rho - \xi_i, \quad i = 1, 2, \dots, l, \quad \rho \geq 0, \xi_i \geq 0, \quad (2)$$

where ξ_i represents a relaxation variable, l represents the amount of variables, w represents the normal vector of the classification hyperplane in the high-dimensional space, b is the constant term, and x_i represents the training set. The parameter v can be used to control the number and error of support vectors. In addition, it is also easier to choose. Parameter ρ represents two types of points (classes -1 and $+1$) that are separated by an interval of $\frac{2\rho}{\|w\|}$.

2.2.2. Leave-One-Out Cross-Validation and Permutation Test

The accuracy of the crack extraction method was verified by the leave-one-out cross-validation and permutation test.

The leave-one-out cross-validation was used to divide a large dataset into k small datasets. Then, $k - 1$ was used as the training set and the other was used as the test set.

Then, the next one was selected as the test set, and the remaining $k - 1$ was selected as the training set. By analogy, the k classification accuracy was obtained and the average value was taken as the final classification accuracy of the dataset.

Using the BG dataset (bare ground dataset) as an example, the data from 400 images of this dataset were divided into 200 groups and each group contained one crack image and one no-crack image. We selected 1 group as the test set and the remaining 199 groups as the training set to obtain a classification accuracy. Then, we selected another group as the test set and the remaining 199 groups as the training set, once again obtaining a classification accuracy. By analogy, each of the 200 groups was used as one test set for machine learning and 200 classification accuracy rates were finally obtained. Their average value was taken as the final classification accuracy of the BG dataset.

Statistically significant p -values were obtained by permutation tests. The permutation test is a method proposed by Fisher that is computationally intensive, uses a random arrangement of sample data to perform statistical inference, and is widely used in the field of machine learning. Its specific use is similar to bootstrap methods by sequentially replacing samples, recalculating statistical tests, constructing empirical distributions, and then inferring the p -value based on this. It assumes that N replacement tests are performed, and the classification accuracy rate obtained by n replacement tests is higher than the true accuracy rate; then, $p\text{-value} = n/N$. When the classification accuracy rate obtained without the replacement test is higher than the true accuracy rate, it is usually recorded as $p\text{-value} < 1/N$: the smaller the p -value, the more significant the difference. In this article, $N = 1000$ permutation tests are performed on the three datasets.

2.3. Image Preprocessing Method

The results of UAV image crack extraction cannot be directly used to calculate feature information, such as the crack length, etc. Therefore, before feature calculation, image preprocessing methods such as skeleton extraction and burr removal are also required.

2.3.1. Skeleton Extraction

Skeletonization (also known as thinning) is an image preprocessing technique that is important in many applications such as pattern recognition, data compression, and data storage [22]. The image skeleton can be considered the result of image thinning. At present, there are many thinning algorithms, such as Hilditch thinning algorithm [23], Pavlidis thinning algorithm [24], etc. It is mainly divided into iterative and non-iterative methods. In iterative methods, a refinement algorithm generates a skeleton by checking and deleting contour pixels in the iterative process in a sequential or parallel manner, and it is also divided into parallel iteration and sequential iteration. Among them, Zhang–Suen algorithm is a parallel iterative algorithm [25] and K3M (Khalid, Marek, Mariusz, and Marcin) algorithm is a sequential iterative algorithm [26]. In this article, K3M algorithm is adopted. The idea of this algorithm is to extract the peripheral contour of the target and to then use the contour to corrode the boundary of the target image until it can no longer be corroded. The crack skeleton was extracted by the K3M method, and the result is shown in Figure 4.

Figure 4. The results of the crack skeleton extraction by K3M: (a) an image of crack extraction; (b) an image of skeleton extraction.

2.3.2. Burr Removal

The current skeleton extraction algorithm usually cannot obtain the idealized crack skeleton, which will produce burrs [27], as shown in Figure 4b. Therefore, it is necessary

to adopt a reasonable method for burr removal. This article proposes a node-based burr removal method.

First, node recognition is performed, as shown in Figure 5, and the skeleton pixel value is 1 and the others are 0. Second, an 8-pixel neighborhood of the skeleton pixel is identified, when the number of skeleton pixels is 1, this skeleton pixel is the endpoint; when the number is 2, this skeleton pixel is the junction point; and when the number is more than 2, this skeleton pixel is an intersection point. Third, branch length identification is performed on all skeleton intersection points to obtain the number of skeleton pixels in each branch. Fourth, setting a threshold, when the number of branch skeleton pixel is less than the threshold, this branch is considered a burr and removed, as shown in Figure 6c₁; when there are multiple branches with a skeleton pixel greater than the threshold, the branch is reserved, as shown in Figure 6c₂.

Figure 5. Node recognition.

Figure 6. The results of burr removal from a skeleton image. (a₁, a₂) are original images, (b₁, b₂) are images of crack extraction, (c₁, c₂) are images of skeleton extraction, and (d₁, d₂) are images of skeleton burr removal.

It should be noted that the threshold is usually close to the crack width. This is because burrs appear in the width direction of the crack, and their length usually does not exceed the crack width.

2.3.3. Intersection-Point Processing

The phenomenon of cracks branching and intersecting is inevitable, and this brings greater difficulties to the acquisition of feature information such as the number, length, width, and direction of surface cracks. Therefore, this article adds the step of intersection-point processing in data preprocessing. The purpose is to break the branching and intersecting cracks such that there are only two node types in the skeleton pixels, as shown in Figure 7: endpoint and junction point. Although this method will cause a small part of the crack to lose a length of 1 pixel, the length of the crack is usually much larger than 1 pixel and, thus, the error is negligible. At the same time, this can greatly reduce the complexity of the calculation method for crack feature information.

Figure 7. The result of intersection-point processing on the skeleton image after removing burrs: (a) an image of skeleton burr removal; (b) an image of intersection-point processing.

2.4. Quantitative Acquisition Method of Crack Feature Information

2.4.1. Crack Length

The crack length is calculated using the skeleton image. As shown in Figure 8, the black line segment represents the particle distance L_i of adjacent pixels. For the endpoint pixels, there are two situations in the 8-pixel neighborhood of the skeleton pixel, as shown in Figure 8 L_1 , L_2 , the particle distances are $L_1 = 1$ pixel and $L_2 = \sqrt{2}$ pixels. For the junction-point pixels, there are three situations in the 8-pixel neighborhood of the skeleton pixel, as shown in Figure 8 L_3 – L_5 , the particle distances are $L_3 = 2$ pixels, $L_4 = 1 + \sqrt{2}$ pixels, and $L_5 = 2\sqrt{2}$ pixels.

Figure 8. The particle distance of an 8-pixel neighborhood of the skeleton pixel.

The equation for crack length is

$$L = l \left(\sum_{t=1}^5 N_t L_t / 2 + \frac{N_1 L_1 + N_2 L_2}{2} \right) \quad (3)$$

where l is the true length of a single pixel, N_t and L_t represent the number of skeleton pixels and the particle distance in different situations, and the value of t ranges from 1 to 5.

2.4.2. Crack Width

Crack width refers to the number of pixels in the vertical direction of the crack along the strike. Any pixel on the crack skeleton has a width value. Therefore, on the basis of the above method for crack length, the width of each skeleton pixel is calculated separately. The calculation method is shown by the black two-way arrow in Figure 9 below, and finally, the average value is taken as the crack width.

Figure 9. Statistical direction of crack width.

In particular, when the 8-pixel neighborhood of the skeleton pixel is shown in Figure 10 W_4 , the width is half the sum of the two vertical crack pixels as the pixel value of the skeleton pixel. In other cases, the width direction is the vertical or angled direction of the particle distance.

Figure 10. Statistical direction and calculation method for crack width (red pixels are skeleton pixels, and yellow pixels are crack pixels): (a) the original crack image, (b) the crack extraction image, (c) the skeleton extraction image, (d) the table form of the crack extraction and skeleton extraction results, (e) the result of node recognition and width statistical direction of each skeleton pixel, (f) the calculation method for crack width, and (g) the resulting crack width.

Example: as shown in Figure 10, it can be seen that the width of the first pixel point of this crack is 5 pixels, that of the second is 4 pixels, that of the third is 4 pixels, etc. The calculation result of the average crack width is 3.36 pixels.

2.4.3. Crack Direction

This article proposes a method for calculating the crack direction based on the regression equation, taking true north as the y -axis, true east as the x -axis, and any one point as the origin to establish a rectangular coordinate system. The skeleton extraction diagram in Figure 10c is converted into the rectangular coordinate diagram shown in Figure 11, and the regression equation is calculated using Equations (4)–(6) with $y = 3.9053x - 119.46$. The crack direction α is calculated using Equation (7), and its value is 14.4° .

$$\hat{b} = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2} \quad (4)$$

$$\hat{a} = \bar{y} - \hat{b} \bar{x} \quad (5)$$

$$\hat{y} = \hat{b}x + \hat{a} \quad (6)$$

$$\alpha = \frac{180^\circ}{2} - \arctan \hat{b} \quad (7)$$

2.4.4. Crack Location

The crack location is of great significance for land reclamation. In this article, the center point of the crack skeleton is used as the parameter crack location. As shown in Figure 12, the middle point A of the image represents the shooting position of the UAV and its latitude and longitude are x_A and y_A , respectively, which can be obtained through the image parameters. The middle point of crack B represents the center point of the crack skeleton. The number of pixels between middle point A and middle point B of the image along the longitude and latitude directions is $\pm m$ and $\pm n$ ($\pm$ represents the direction; when B is located to the east or north of point A, use +, and when B is located to the west or south of point A, use -).

south of point A, take $-$), the ground sampling distance (GSD) is l ; p and q are the true distances represented by 1° of longitude and latitude, respectively; and then, the longitude and latitude are calculated from the middle of crack B:

$$\begin{cases} x_B = x_A \pm nl/p \\ y_B = y_A \pm ml/q \end{cases} \quad (8)$$

Figure 11. The result of converting the skeleton pixels to the rectangular coordinate diagram.

Figure 12. The crack location in a UAV image.

2.4.5. Crack Fractal Dimension

Fractal dimension can be used as a measure of image texture roughness, and it is widely used in the extraction of cracks [28]. The fractal dimension of the linear features of surface cracks and similar linear features in the image are accurately calculated and can better extract the feature information of surface cracks. Commonly used fractal dimensions include Hausdorff dimension, Box Counting dimension (box dimension), Minkowski–Bouligand dimension, etc. [29]. This article uses the box dimension to calculate the fractal dimension of the crack. Its definition is shown in the following Equation (9). The graph is divided into small boxes, where r is the value of the side length of the box in the side length of the graph, and N_r is the number of boxes occupied by the crack. We calculate N_r for different r and apply the least square to fit the array $(\log(\frac{1}{r}), \log(N_r))$, as shown in Equations (10)–(12), where the fractal dimension $D = \beta$.

$$D = \lim_{r \rightarrow 0} \left(\frac{\log(N_r)}{\log\left(\frac{1}{r}\right)} \right) \quad (9)$$

$$y = \alpha + \beta x \quad (10)$$

$$\alpha = \frac{\sum \log(N_r)}{n} - \beta \frac{\sum \log\left(\frac{1}{r}\right)}{n} \quad (11)$$

$$\beta = \frac{\frac{\sum (\log(N_r) \log(\frac{1}{r}))}{n} - \frac{\sum \log(N_r) \sum \log(\frac{1}{r})}{n}}{\frac{\sum (\log(\frac{1}{r}))^2}{n} - \left(\frac{\sum \log(\frac{1}{r})}{n}\right)^2} \quad (12)$$

2.4.6. The Number of Cracks

Based on MATLAB's bwlabel function, the number of connected components is n . Then, based on the node recognition results, the number of intersection points is m . Therefore, the number of cracks is the sum of m and n . As shown in Figure 13, the statistics show that the connected components n is 2, the intersection point m is 1, and the number of cracks is 3.

Figure 13. A skeleton extraction image of intersecting crack.

2.4.7. Crack Rate and Dispersion Rate

In order to comprehensively reflect the distribution characteristics of cracks, the crack rate is usually used as the crack measurement and analysis index. The crack rate is the percentage of the crack area to the study area. However, this method cannot adequately reflect the distribution of a crack. As shown in Figure 14, with two distributions of multiple cracks in Figure 14a,b, the crack rates are calculated as the same, but it can be seen from the figure that there are obvious differences in the distribution of cracks in the two situations; therefore, only the crack rate cannot reflect the true distribution of regional cracks.

Figure 14. Two distributions of multiple cracks. (a) shows the scattered distribution of three cracks, (b) shows the concentrated distribution of three cracks.

In view of this, this article proposes a method for calculating the dispersion rate, which reflects the distribution of cracks in the study area through a combination of the crack rate and the dispersion rate. The crack rate shows the size of the crack area, which is also called the areal density of the crack. Its calculation method is the ratio of the crack area to the image area, as shown in Equation (13). The dispersion rate shows the dispersion of cracks, reflecting that the distribution of the cracks is relatively concentrated or scattered. The calculation method is as follows:

The first step is to obtain the center point $(\bar{x}, \bar{y})$ of all the crack pixels. The second step is to calculate the average Euclidean distance D/S between all the crack pixel points and the crack center point. The third step is to perform normalization. Theoretically, the maximum average Euclidean distance will not exceed half of the diagonal length of the image. Therefore, the ratio of the average Euclidean distance to half of the diagonal length of the image is used as the normalized dispersion rate. As shown in Equations (14)–(18), the essence of the dispersion rate is the average Euclidean distance between all crack pixels and the center point normalized: the lower the value, the closer all the skeleton points are to the center point and the more concentrated the distribution, and the higher the value, the farther all the crack points are from the center point and the more scattered the distribution.

$$\delta = \frac{1}{a \times b} \sum_{i=1}^n A_i \quad (13)$$

$$\bar{x} = \sum_{i=1}^m \sum_{j=1}^{n_i} x_{ij} \quad (14)$$

$$\bar{y} = \sum_{i=1}^m \sum_{j=1}^{n_i} y_{ij} \quad (15)$$

$$S = \sum_{i=1}^m n_i \quad (16)$$

$$D = \sum_{i=1}^m \sum_{j=1}^{n_i} \sqrt{(x_{ij} - \bar{x})^2 + (y_{ij} - \bar{y})^2} \quad (17)$$

$$\sigma = \frac{D/S}{\sqrt{a^2 + b^2}/2} \quad (18)$$

where a and b represent the length and width of the image, respectively; i represents the crack number; j represents the pixel of each crack; x_{ij} and y_{ij} represent the coordinates of any crack pixel in the plane rectangular coordinate system; m represents the number of cracks; n_i represents the number of crack pixels of the i th crack; $\bar{x}$ and $\bar{y}$ represent the coordinates of the crack center point in the rectangular coordinate system; S represents the number of all crack pixels; D represents the sum of the Euclidean distance of all crack pixels and the crack center; A_i represents the area of the i th crack; σ represents the normalized dispersion rate; and δ represents the crack rate. The range of the two values is between 0 and 1.

Figure 14a,b have the same crack rate δ . By calculating the dispersion rate $\sigma_a = 0.3016 > \sigma_b = 0.1874$, the distribution of cracks in Figure 14a is more dispersed than that in Figure 14b, which is consistent with what the image shows. It is proven that this method can be used to reflect the dispersion degree of the cracks.

3. Results and Discussion

3.1. Results of Crack Extraction

This article proposes a method for crack extraction of UAV images based on machine learning. The machine learning method uses SVM, and the dimensionality reduction method uses F-score. The parameter selection of the F-score is 0.1:0.1:1, which means that, according to the weight/F value, the first 0.1 features are selected first, then 0.1 is used as the step size, and the features are selected gradually to 1 (100%). The verification method uses leave-one-out cross-validation and the permutation test. The number of permutation tests is 1000.

The results are shown in Figure 15 and Table 2. We can find that, for the three datasets, when full feature selection is used for the image, the classification accuracy and AUC value are the largest, and the p -value is less than 0.001, which proves that machine learning can

effectively classify whether there are cracks in the UAV sub-images. Among them, the classification accuracy of the bare land dataset reached 87.75%, the classification accuracy of the soil crust dataset reached 87.25%, and the classification accuracy of the green vegetation dataset reached 93.50%. The overall accuracy rate reached 89.5%.

Figure 15. The results of leave-one-out cross-validation and the permutation test. BG is the bare ground dataset, SC is the soil crust dataset, and GV is the green vegetation dataset. (a) is the accuracy change result for different dimension selection, (b) is the result of ROC curve and its AUC value, (c) is the result of the permutation test.

Table 2. Final classification results.

Dataset	Background Information	Number of Training Sample	Number of Correct Classifications	Accuracy	AUC
BG	Bare Ground	400	351	87.75%	0.8802
SC	Soil Crust	400	349	87.25%	0.9431
GV	Green Vegetation	400	374	93.50%	0.9983
Total	ALL	1200	1074	89.50%	

Through the above method, the UAV sub-images are divided into two categories: cracks and no cracks. For crack images, the crack extraction method of threshold segmentation is used. For no crack images, the black background method is used. Finally, each processed image is stitched together, and the final UAV image crack extraction effect is shown in Figure 16b.

Figure 16. Image preprocessing results: (a) a UAV image synthesized through the RGB band, (b) the result of crack extraction, (c) a skeleton image after data preprocessing, and (d) the comparison of the final schematic diagram of the crack extraction effect in the UAV image and original UAV image.

3.2. Image Preprocessing Results

The crack extraction image obtained above is performed by skeleton extraction, burr removal, and intersection-point processing, as shown in Figure 16c, which provides data support for subsequent quantitative acquisition of crack feature information.

3.3. Quantitative Calculation Results of Crack Feature Information

3.3.1. Single Crack Feature Calculation Results and Accuracy Verification

The single crack features include crack length, average width, direction, location, and fractal dimension. The statistics for crack length and direction use the skeleton image after data preprocessing. The crack width, location, and fractal dimension use the crack extraction image.

The true value measurement method for the crack feature information is as follows: the true value of the crack length is measured by the traverse method. The true value of the crack width is obtained by measuring the width of five different parts of the crack and by taking the average value. The true value of the crack direction is determined by the compass. The true value of location is measured by a handheld GPS (Global Positioning System). In this study area, five cracks at different locations were randomly selected for accuracy verification by comparing the true value and the image value calculated. As shown in Figure 17.

The results of the image calculation values and field measurement values are shown in Table 3. We can find that all the crack length errors are less than 10%, that the crack width errors are less than 19%, that the direction difference is less than 3° , and that the location distance difference is less than 3 m. This shows that the results calculated by the method in this article are relatively close to the true value, which is an effective method for crack feature information calculation.

Figure 17. Five cracks at different locations were randomly selected for accuracy verification in this study area.

Table 3. The comparison result of crack feature extraction and true value measurement.

Crack	Value	Length/m	Width/m	Direction	Longitude	Latitude
1	Image	0.359	0.026	14.0°	110°13'41.178531"E	39°4'44.335786"N
	True	0.327	0.022	15.0°	110°13'41.193426"E	39°4'44.342607"N
	Error	9.8%	18.2%	1°	0.202 m	
2	Image	0.296	0.015	10.7°	110°13'40.746874"E	39°4'43.968457"N
	True	0.280	0.013	12.0°	110°13'40.787633"E	39°4'43.985143"N
	Error	5.7%	15.4%	1.3°	1.446 m	
3	Image	0.974	0.038	40.4°	110°13'40.771399"E	39°4'43.251318"N
	True	0.925	0.034	42.0°	110°13'40.781512"E	39°4'43.271282"N
	Error	5.3%	11.8%	1.6°	0.451 m	
4	Image	1.079	0.030	18.2°	110°13'41.945486"E	39°4'43.885978"N
	True	1.040	0.027	20°	110°13'41.996862"E	39°4'43.914026"N
	Error	3.8%	11.1%	1.8°	2.624 m	
5	Image	0.525	0.033	13.1°	110°13'41.288752"E	39°4'43.778758"N
	True	0.506	0.030	16.0°	110°13'41.338136"E	39°4'43.806915"N
	Error	3.8%	10.0%	2.9°	2.487 m	

3.3.2. Regional Crack Feature Calculation Results

Regional crack feature refers to the characteristics reflected by all cracks in the study area, including the number of cracks, crack rate, and dispersion rate. The statistics for the number of cracks use the skeleton image after data preprocessing. The crack rate and dispersion rate use the crack extraction image. The results are shown in Table 4.

Table 4. The results of regional crack feature calculation.

Image Size/Pixel	Number of Crack/Pixels	Crack Number	Crack Rate (δ)	Dispersion Rate (σ)
4000 × 3000	15,417	92	0.13%	0.2128

All of the cracks in the study area were calculated. The statistical results for crack length and crack width are shown in Figure 18. We can see that the crack length is mainly within 5 m, accounting for 96.74%, and that the crack average width is mainly within 0.04 m, accounting for 95.65%. The statistical results of the crack direction are shown in Figure 19. The number of cracks is counted at 15° intervals. We can see that the crack direction is

generally in the north–south direction. The statistical results of the crack fractal dimension are shown in Figure 20, from which we can see that the crack fractal dimension is between 1.0750 and 1.3521. The surface cracks show an excellent linear correlation, which shows that the regional surface cracks in this image have good statistical self-similarity. It has a good fractal geometry structure. The calculated result of box dimension shows that coal mining surface cracks have fractal dimensions. To a certain extent, surface cracks do not exist in isolation and have systems with similar or identical features inside. This conclusion is consistent with Mao Cuilei’s conclusion in the study of the distribution characteristics of surface cracks, and his result showed that the fractal box dimension of surface cracks in the region is between 1.08–1.35 [30].

Figure 18. The statistical results for crack length and crack width.

Figure 19. The statistical result for all crack directions.

Figure 20. The statistical result for all crack fractal dimensions.

4. Conclusions

This article proposes a surface crack extraction method based on machine learning of the UAV image, the data preprocessing steps, the content of the crack feature information, and the calculation method. The reliability of the method is proven by accuracy verification, and the following conclusions are obtained:

1. The error in surface crack extraction from a UAV image mainly comes from complex background information such as vegetation and soil crust. Using machine learning to classify the sub-images, then to extract cracks, and to re-splice is an effective method to avoid the error. The total accuracy reached 89.50%.
2. By acquiring the single crack feature information content—crack length, width, direction, fractal dimension, and location—it can clearly describe the feature information of any crack. In this study area, the crack length is mainly within 5 m, the crack average width is mainly within 0.04 m, the crack direction is generally in the north–south direction, and the crack fractal dimension is between 1.0750 and 1.3521.
3. The concept and calculation method for the dispersion rate are introduced. The crack rate is used to show the size of the crack area, and the dispersion rate is used to show the concentration or dispersion of the cracks in the area. This method more clearly and completely describes the distribution characteristics of regional cracks.

Cracks are a common geological disaster. The scientific repair of cracks requires us to reasonably classify and evaluate different degrees of cracks. This article not only achieves higher-precision crack extraction but also obtains a reliable quantitative calculation method for crack feature information, which can provide data support for further research on the development and risk evaluation of surface cracks. Furthermore, we will use the crack feature information as the evaluation index and the value obtained by quantitative calculation as the evaluation basis to evaluate the damage degree of the crack and then propose a reasonable repair plan.

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