

Article

A Surface Crack Damage Evaluation Method Based on Kernel Density Estimation for UAV Images

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Abstract: The development of UAV (unmanned aerial vehicle) technology provides an ideal data source for the information extraction of surface cracks, which can be used for efficient, fast, and easy access to surface damage in mining areas. Understanding how to effectively assess the degree of development of surface cracks is a prerequisite for the reasonable development of crack management measures. However, there are still no studies that have carried out a reasonable assessment of the damage level of cracks. Given this, this article proposes a surface crack damage evaluation method based on kernel density estimation for UAV images. Firstly, the surface crack information from the UAV images is quickly and efficiently obtained based on a machine learning method, and the kernel density estimation method is used to calculate the crack density. The crack nuclear density is then used as a grading index to classify the damage degree of the study area into three levels: light damage, moderate damage, and severe damage. It is found that the proposed method can effectively extract the surface crack information in the study area with an accuracy of 0.89. The estimated bandwidth of the crack kernel density was determined to be 3 m based on existing studies on the effects of surface cracks on soil physicochemical properties and vegetation. The maximum crack density value in the study area was 316.956. The surface damage area due to cracks was 14376.75 m². The damage grading criteria for surface cracks in the study area (light: 0–60; moderate: 60–150; severe: >150) were determined based on the samples selected from the field survey by crack management experts. The percentages of light, moderate, and severe damage areas were 72.77%, 23.22%, and 4.01%, respectively. The method proposed in this article can effectively realize the graded damage evaluation of surface cracks and provide effective data support for the management of surface cracks in mining areas.

Keywords: UAV; surface crack; nuclear density estimation; damage evaluation



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1. Introduction

The mining of coal resources is necessary to support the smooth growth of the social economy, but doing so underground has resulted in significant ecological and environmental issues [1,2]. Surface cracks are one of the environmental issues brought on by coal mining in western China, particularly in the arid and semi-arid regions [3], which also results in building deformation, destruction of arable land, accelerated soil moisture evaporation, vegetation destruction, and soil erosion [4–6]. Additionally, it was discovered that cracks of various widths had a variety of noteworthy impacts on soil water content and soil respiration [7]. Therefore, in order to assess the degree of damage and crack development in the study area and to provide data support and assurance for land reclamation work, it is necessary to first obtain real-time, objective, and high-precision distribution information of surface cracks in the mining area [8]. This information must also be acquired and quantitatively described.

Surface crack extraction through UAV (unmanned aerial vehicle) images has achieved wide application [9]. UAVs have significant advantages such as a high resolution, flexibility and mobility, high efficiency and speed, and low operating costs [10], providing an ideal data source for information extraction of surface cracks in mining areas. The current methods for surface crack extraction through UAV images are mainly object-oriented [11,12], edge detection [13], threshold segmentation [14], manual visual interpretation [15], etc. Some scholars have also conducted experimental studies based on image processing and pattern recognition techniques to achieve crack measurement and statistical aspects with some results [16,17]. However, these studies are mainly based on image processing to extract information about cracks from UAV images. There is no mature method for evaluating the damage of cracks in coal mining subsidence areas, which would be useful for the data support of land reclamation and treatment plan design, so there is an urgent need to propose a more reliable method for evaluating the damage of cracks.

To solve the above problems, this article proposes a new surface crack damage evaluation method using the kernel density estimation method commonly used in geographic information analysis [18]. KDE (kernel density estimation) in two dimensions has been widely used in the field of geographic information analysis research and is an effective tool for spatial clustering analysis, hotspots, or risk point identification [19–21]. In this article, we use the kernel density estimation method to construct an evaluation method for surface crack damage caused by mining in the arid and semi-arid areas of Yulin city in northern Shaanxi Province, using the coal mining area as the study area. First, we obtain high-precision crack extraction results based on machine learning methods. Then, we calculate the surface crack nucleus density in the study area and take it as a grading index. Finally, combined with the results of the field investigation by crack management experts, the classification assessment of cracks is carried out. The damage degree of the study area is divided into three levels: light damage, moderate damage, and severe damage.

The rest of the article is organized as follows: Section 2 presents the materials and methods, Section 3 presents the results, Section 4 provides a discussion, and the final section draws the conclusions.

2. Materials and Methods

2.1. Data Source

The study area is located in the Ningtiao Coal Mine ($38^{\circ}58'–39^{\circ}6' \text{ N}$, $110^{\circ}9'–110^{\circ}17' \text{ E}$), Shenmu city, Shaanxi Province, China (Figure 1a,b), which lies on the southeastern edge of the Mu Us Desert (Figure 1), and the surface cracks originated from the exploitation of underground high-intensity coal resources. The study area is a typical arid aeolian sand area, with little vegetation, mainly low shrubs and herbs. The average annual precipitation in the study area is about 434.1 mm, and the average annual temperature is 8.6°C . After underground coal mining, the surface of the study area moved and deformed, resulting in a large number of cracks, which can be easily seen in the ground survey and UAV images (Figure 2).

We used the DJI Matrice 210 RTK equipped with a Zenmuse X5S camera to obtain high-resolution images of the study area. During our flight campaign, the parameters of the UAV and camera were set as shown in Table 1, and we used DJI GS Pro software to operate the drone flight. After removing the images with poor imaging quality, such as those with blur and color cast, Pix4D mapper software was used to process the UAV image to produce the digital orthophoto map (DOM) of the study area with a resolution of 0.013 m (Figure 3).

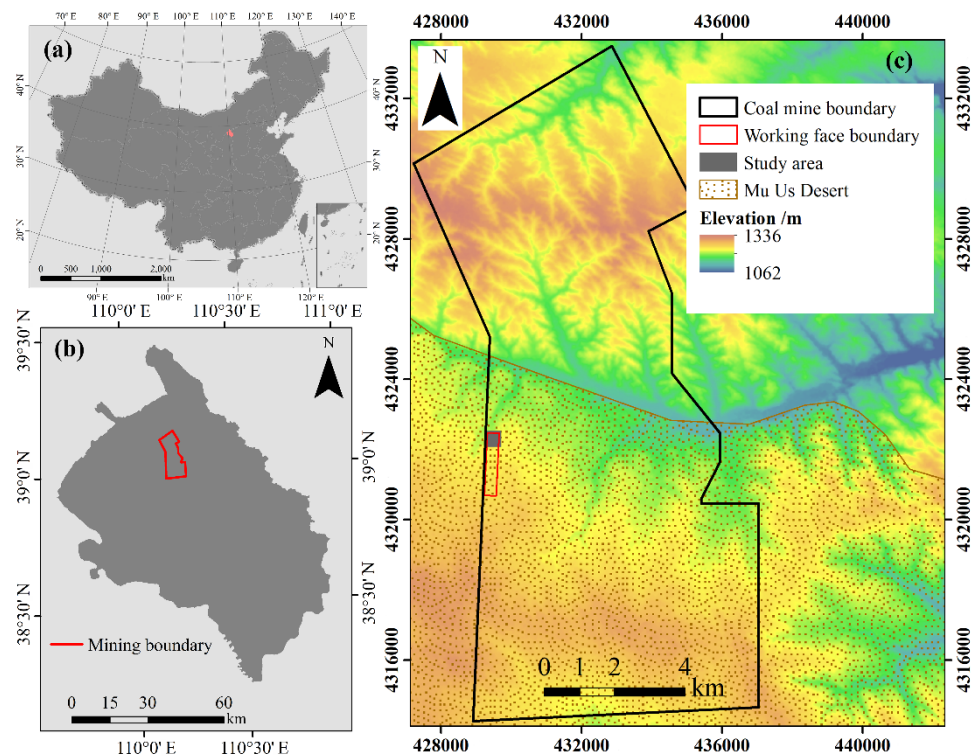


Figure 1. The geographical location of the study area and study subjects: (a,b) locations of Shenmu County and Ningtiaota coal mine, where the study area is located, in China; (c) topography of the study area.

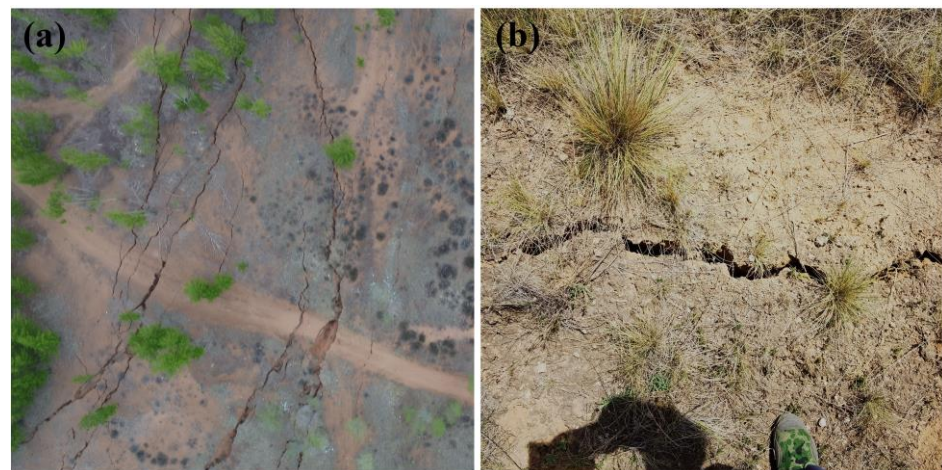


Figure 2. The morphology of surface cracks in the study area: (a) acquired using a UAV; (b) acquired using a mobile phone.

Table 1. The parameters of the UAV and camera in our flight campaign.

Parameters	Value
Data types	Visible image
Flight date	7 May 2020
Flight altitude	50 m
Overlap	80% (front), 60% (side)
Camera type	Zenmuse X5S
Focal length	15 mm
Ground sampling distance (GSD)	0.011 m

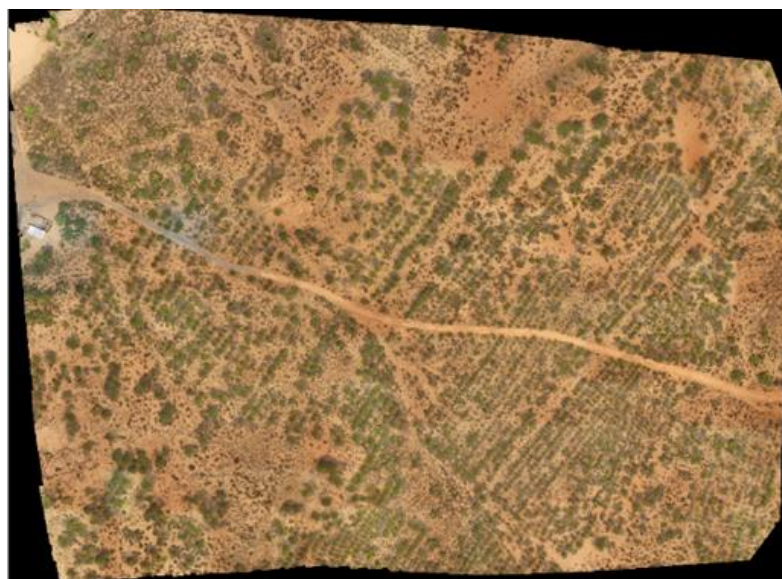


Figure 3. Unmanned aerial vehicle (UAV) image data.

2.2. Research Method

This article proposes a surface crack damage evaluation method based on nuclear density estimation for UAV images, and its flow chart is shown in Figure 4. Firstly, the UAV images were acquired and cracks were extracted. Secondly, the kernel density estimation method was used to calculate the density of the study cracks. Then, the kernel density of the surface crack was used as the basis, combined with the field survey results of the crack management experts, to determine the grading index. Finally, the damage degree of the study area was evaluated.

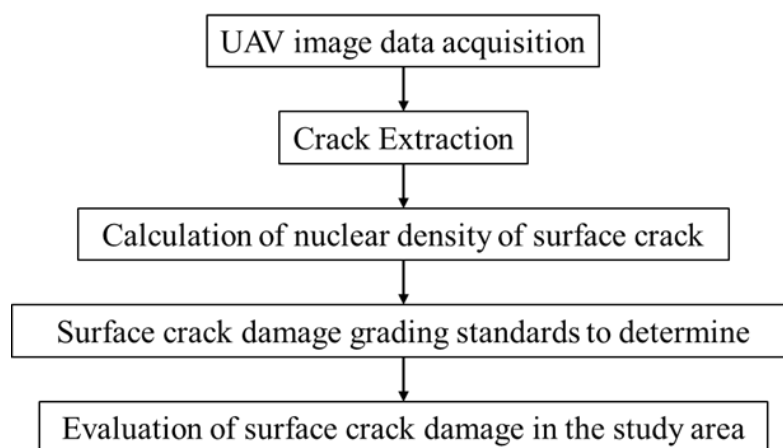


Figure 4. Flow chart of surface crack damage evaluation method.

2.3. UAV Image Crack Extraction Method

The geological environment of the mining area is complex, and the surface vegetation is overgrown; furthermore, the spectral color characteristics of the ground withered vegetation and surface cracks are similar, resulting in a low accuracy and efficiency in extracting cracks based on UAV images. In recent years, scholars have gradually applied artificial intelligence methods to image recognition and crack detection with good results. For the extraction of surface cracks in the mining area, Zhang Fan et al. [22] cut the complete UAV image into small sub-images for crack extraction through image cutting, which effectively avoided the interference of vegetation and obtained better results. Therefore, this article proposes a crack extraction method based on machine learning for UAV sub-images considering

this method. First, MATLAB was used to convert the UAV image into sub-images with cut pixels of 50×50 . Second, the sub-images containing cracks were identified by the support vector machine (SVM) machine learning method, the dimensionality reduction method via PCA (principal component analysis), and the image enhancement method via Laplace sharpening, and the crack extraction results of the sub-images were obtained using the threshold segmentation method. Third, the sub-images that do not contain cracks were image-processed to make their background black. Fourth, all processed images were restitched according to the original cut sequence number, obtaining the final UAV image crack extraction results. Fifth, the kappa coefficient method was used to evaluate the crack extraction accuracy, and 2000 sample points were randomly selected, with 1000 crack pixels and no-crack pixels each, and the manual visual interpretation results were used as the true values to verify the accuracy of the crack extraction results. The specific SVM, PCA, Laplace sharpening, and threshold segmentation methods are described in detail below.

A support vector machine [23] is a type of generalized linear classifier that performs binary classification of data according to supervised learning, and its decision boundary is the maximum margin for solving the learning sample, i.e., the maximum margin hyperplane. C-SVM is a support vector machine algorithm with parameter C as a penalty function. It is a two-category classification model [24]. It is defined as the linear classifier with the largest interval in the feature space. The learning strategy is margin maximization. This translates into a solution to a convex quadratic programming problem. For linearly separable cases, the C-SVM problem can be transformed into the following quadratic programming problem:

$$\min \quad \|w\|^2 + C \sum_{i=1}^l \xi_i \quad (1)$$

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

where C is a penalty parameter: the larger C is, the more the SVM punishes the incorrect classification, and C is the only adjustable parameter in C-SVM; ξ_i represents a relaxation variable; l represents the number of variables; w represents the normal vector of the classification hyperplane in the high-dimensional space; b is the constant term; x_i represents the training set. Support vector machines are one of the most commonly used binary classification machine learning methods. By properly selecting their parameters, they can effectively judge and identify whether the UAV sub-image has cracks.

Dimensionality is the number of feature vectors in the image. More than three feature vectors perpendicular to each other represent a high-dimensional space that cannot be visualized. When the dimensionality increases, the volume of space increases too quickly and thus the available data become sparse. To obtain statistically correct and reliable results, the amount of data needed to support this result usually increases exponentially with the number of dimensions. On the other hand, due to the existence of Eigen dimensions, the concept is that any low-dimensional data space can be transformed into a higher-dimensional space simply by adding a spare (e.g., replication) or random dimension, and conversely, many data sets in high-dimensional spaces can be reduced to low-dimensional data without losing important information.

When the dimension is higher, the amount of information contained is larger, and the classification difficulty of the machine learning algorithm is also greater. When the dimension exceeds a certain value, the curse of dimensionality occurs [25]. At this time, dimensionality reduction is needed to achieve the best classification effect. Principal component analysis is a dimensionality reduction method often used in image processing [26]. The steps are as follows:

First, input the sample set $D = \{x_1, x_2, \dots, x_m\}$ and map it to the low-dimensional (k -dimensional) space dimension. Second, transform the samples in X to the standard normal distribution $N \sim (0,1)$. Third, find the covariance matrix $X^T X \in \mathbb{R}^m \times m$ and solve the eigenvalues and eigenvectors of the covariance matrix, $X^T X = V \times \Sigma \times V^{-1}$. Fourth, find the maximum k eigenvalues and the corresponding eigenvectors, record them as $(\omega_1, \omega_2, \omega_3 \dots \omega_k)$, and output them as $W = \{\omega_1, \omega_2, \omega_3 \dots \omega_k\}$.

Before performing machine learning, images are usually preprocessed first, in which image enhancement methods are widely used. Image enhancement is a common image-processing method. It can emphasize the local features of an image [27]. Laplace sharpening is an image color-enhancement method that can effectively enhance the crack information of the land in the mining area and has achieved a good classification effect.

The Laplace operator [28] is an edge detection operator. The effect of this operator on $f(x,y)$ is

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (3)$$

From the sharpening formula of the one-dimensional signal, the sharpening formula of the two-dimensional digital image is

$$g(m,n) = f(m,n) + \alpha \left[-\nabla^2 f(m,n) \right] \quad (4)$$

In digital image processing, $\frac{\partial^2 f}{\partial x^2}$ and $\frac{\partial^2 f}{\partial y^2}$ can be expressed as a differential equation as

$$\frac{\partial^2 f}{\partial x^2} = f(m+1,n) + f(m-1,n) - 2f(m,n) \quad (5)$$

$$\frac{\partial^2 f}{\partial y^2} = f(m,n+1) + f(m,n-1) - 2f(m,n) \quad (6)$$

By adding Equations (5) and (6) into $g(m,n)$, the Laplacian sharpening expression is

$$g(m,n) = (1 + 4\alpha)f(m,n) - \alpha[f(m,n+1) + f(m,n-1) + f(m+1,n) + f(m-1,n)] \quad (7)$$

where α is the sharpening intensity coefficient. The larger the α , the stronger the sharpening degree, and the larger the “overshoot” corresponding to the figure.

Threshold segmentation [29] is a region-based image segmentation technique based on the principle of dividing image pixel points into several classes. The advantages of threshold segmentation are its simple calculation, high operational efficiency, and speed, and it has been widely used in various image recognition fields. The crack extraction method based on threshold segmentation is based on the grayscale difference between the crack target and background information to be extracted in the image, and it classifies the pixels by setting a threshold.

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq T \\ 0 & \text{if } f(x,y) < T \end{cases} \quad (8)$$

where $f(x,y)$ is the gray pixel value of the original image, $g(x,y)$ is the gray pixel value of the crack extraction image, and T is the gray threshold.

2.4. Kernel Density Estimation Method

Kernel density estimation (KDE) [30] is a nonparametric estimation method used to estimate the probability density function and has applications in many research neighborhoods. KDEs in two dimensions are mainly estimated with the help of a moving cell (sliding window) for the density of a point or line pattern [31]. To effectively address different research components, KDE methods exist in various forms depending on the kernel function used [19]. The KDE method used in this paper is the one proposed by Silverman [32], whose expression is

$$\hat{\lambda}_h(s) = \sum_{i=1}^n \frac{3}{\pi h^4} \left(1 - \frac{(s-s_i)^2}{h^2} \right)^2 \quad (9)$$

where $\hat{\lambda}_h(s)$ is the kernel density of the surface crack at position s ; h is the search radius of the KDE, that is, the bandwidth, and only the crack in the bandwidth is involved in the calculation of the kernel density at s ; and s_i is the location of the surface crack. It should be noted that the surface crack results extracted in Section 2.3 are surface elements in raster form and not point or line elements as commonly used in KDE analysis. Therefore, the extracted crack results are converted to vector point elements for further processing in this article.

In the process of KDE analysis, a reasonable bandwidth h selection is very important. h determines the smoothness of the spatial distribution of the kernel density, and the larger the h , the smoother the density distribution. In existing geographic information analysis studies, reasonable bandwidths are often determined based on the degree of focus on clustering features and local features from a global perspective [33]. In this research, there is a range of impacts of surface cracks on the surrounding surface ecology, so the size of the bandwidth h cannot be set arbitrarily.

The surface damage caused by surface cracks in coal mining subsidence areas mainly comes from the changes in soil physicochemical properties and mechanical damage to vegetation roots caused by them [34–36]. In a study of the effect of surface cracks on soil moisture in the adjacent mine in the study area of this paper, Yingbin Ma found that the surface cracks did not affect more than 1.5 m, while the aboveground biomass of vegetation was affected within 3 m around the cracks [37]. In a study on the effect of coal mining subsidence cracks on soil physical and moisture properties in wind and sand areas, Han Zhenying found that there was a more significant difference between the 2 m range on both sides of the cracks and the control area [38]. Xu Chuanyang et al. showed that coal mining subsidence cracks do not affect soil properties and crop growth beyond 1.2 m [39]. The results of Wang Qiangmin et al. showed that the effect of coal mining subsidence cracks on soil moisture transport in the wind and sand areas was not more than 1.5 m [40]. According to the existing research results, this article determined the bandwidth h to be 3 m according to the influence range of coal mining subsidence cracks on the surface.

2.5. Surface Crack Grading Index Determination

There are relatively few studies on the grading index of surface cracks, and Li Yang [41] et al. constructed a hazard evaluation model with thirteen factors, such as the surface crack degree, surface crack activity, distance from the surface crack, hydro-geological conditions, ground settlement, and average annual rainfall, in a study on the hazard zoning of surface cracks in greater Xi'an, and divided the hazard into four levels for each area of Xi'an city. However, the model of its evaluation is mainly based on the risk of cracks in the city, and the study area is large and has more risk factors, which does not apply to a small area with a single impact factor. For the evaluation of the damage of surface cracks affected by mining, the influence factor is mainly the development degree of surface cracks, so this article takes the nuclear density of cracks as the grading index and divides the damage evaluation of cracks into three levels: light damage, moderate damage, and severe damage.

Since no research has been conducted on the grading criteria of ground crack damage evaluation, this study hired experts experienced in surface crack management research to conduct field surveys and selected three sample squares of damage grades in the study area, where each damage grade corresponds to three sample areas with a sample size of $5 \times 5 \text{ m}^2$, as shown in Figure 5. Then, the density of crack nuclei in the interior of the sample squares was counted, followed by an analysis of their statistical characteristics and the determination of the grading criteria for crack damage.

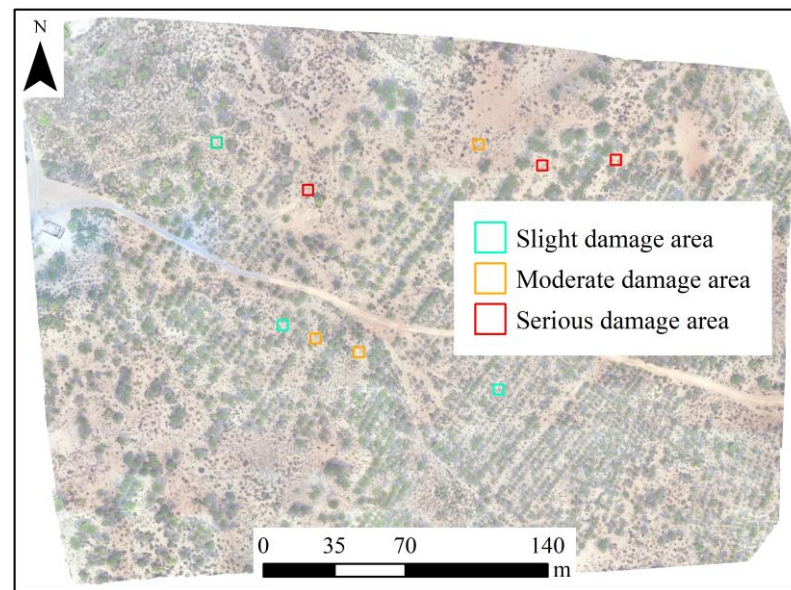


Figure 5. Sample area distribution of surface crack classification index in the study area.

Ideally, the kernel density distributions of the three damage level samples should not intersect each other, but the distribution of surface cracks is usually uneven, and there may be moderate and severe damage areas in the light damage samples. Therefore, the kernel density distribution of the three damage level samples should be as shown in Figure 6.

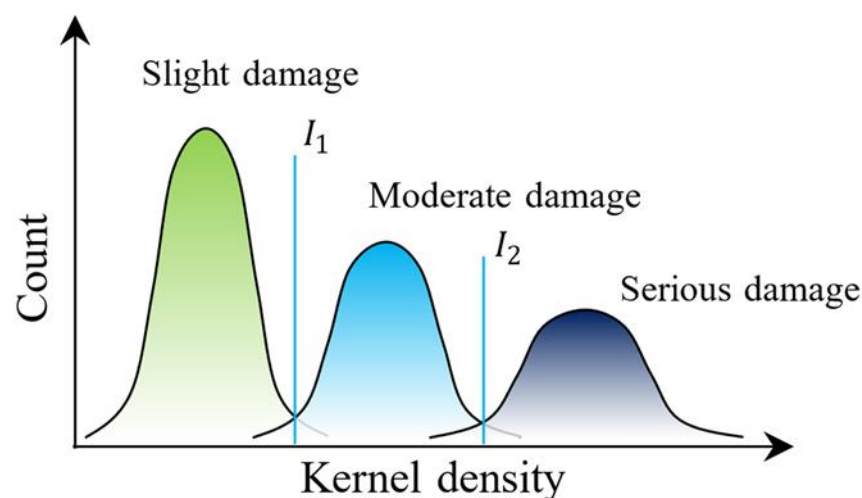


Figure 6. Conceptual map of the distribution of nuclear density and grading criteria for each damage level sample.

Due to the overlap of the kernel density distribution of each damage class, this article determines the classification criteria I_1 for light and moderate damage and I_2 for moderate and heavy damage by estimating the intersection of the kernel density distribution of light and moderate damage, and moderate and heavy damage samples (Figure 6). Then, I_1 and I_2 are used to classify the damage of cracks in the whole study area.

3. Results

3.1. Evaluation of Surface Crack Extraction Results and Accuracy

The surface crack extraction results are shown in Figure 7, and it can be seen that the proposed method can effectively avoid the interference of vegetation and obtain more accurate crack extraction results. Table 2 shows the evaluation results of the surface crack

extraction accuracy. By randomly selecting 1000 crack pixels and 1000 no-crack pixels, 942 correct crack pixels and 838 correct no-crack pixels were obtained based on the comparison of the manual visual interpretation results and crack extraction results, and the accuracy was 0.89.

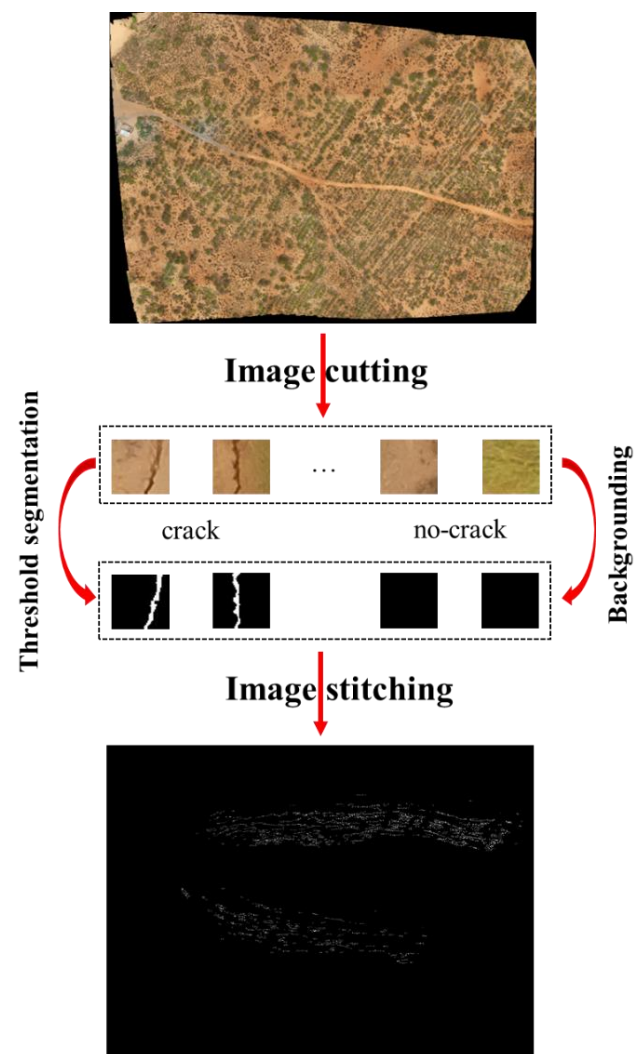


Figure 7. Simplified process of extracting surface cracks from UAV images and the extraction result.

Table 2. Evaluation results of surface crack extraction accuracy.

	Crack	No Crack
All pixels	1000	1000
Correct pixels	942	838

The larger the scope of the UAV image, the more types of surface objects it contains, the more complex the background information of the image, and the more difficult it is to extract cracks. After the complete large-scale UAV image is cut into sub-images of small units, the background information of the sub-image and the types of surface objects it contains are reduced, and less interference is encountered when extracting cracks through threshold segmentation. The accuracy of crack extraction from sub-images is often better than that from complete large-scale UAV images. This is an effective method to avoid the influence of vegetation and other features on crack extraction results.

3.2. Nuclear Density of Surface Crack

In this article, the surface crack data extracted from the UAV images were converted to data types, and the kernel density of surface cracks in the study area was calculated using ArcGIS software with a 3 m bandwidth, while 1 m and 5 m bandwidths were set as comparison experiments. The kernel density calculation results are shown in Figure 8.

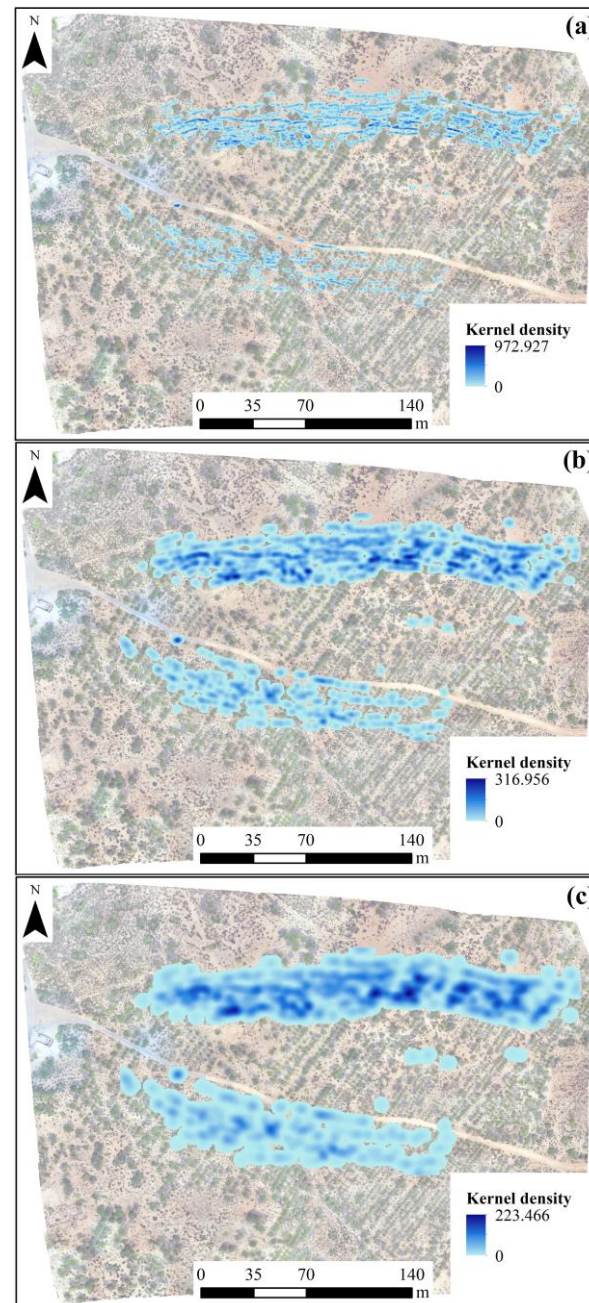


Figure 8. Calculated results of nuclear density of surface cracks: (a) bandwidth of 1 m; (b) bandwidth of 3 m; (c) bandwidth of 5 m.

From Figure 8, the maximum density value of the surface crack is 972.927 when the bandwidth is 1 m, while the corresponding maximum density values are 316.956 and 223.466 when the bandwidth is 3 m and 5 m. The larger the bandwidth, the smoother the variation in the core density of the surface crack in the study area; however, when the damage range of the surface crack is larger, the damage ranges corresponding to the bandwidth sizes of 1 m, 3 m, and 5 m are 6584.75, 14,376.75, and 18,895.75 m², respectively.

The damage areas corresponding to the 1 m, 3 m, and 5 m bandwidths are 6584.75, 14,376.75, and 18,895.75 m², respectively, with large differences. Therefore, this study is different from the geographic information analysis study mentioned in a previous paper, and the bandwidth size cannot be determined according to the expression effect of the density calculation results in the nuclear density estimation process; the bandwidth needs to be determined according to the specific impact range of the surface crack to avoid an incorrect estimation of the damage range of the coal mining subsidence surface crack.

3.3. Surface Crack Damage Grading Standard Determination

Combined with the results of calculating the kernel density of surface cracks in the study area, this article statistically analyzes the distribution of the kernel density in the three damage level samples selected in the field survey conducted by crack management experts, and the statistical results of the density of cracks in each sample are shown in Figure 9.

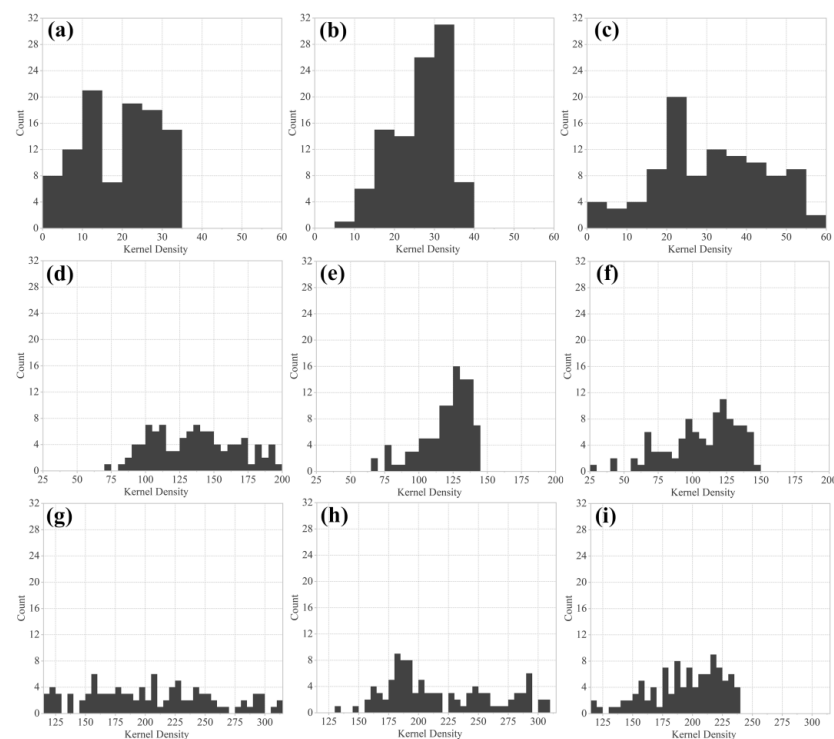


Figure 9. Crack density statistics for each damage level sample: (a–c) lightly damaged samples; (d–f) moderately damaged samples; (g–i) severely damaged samples.

From Figure 9, we can see that the distribution of the nuclear density of cracks in the interior of the sample with a low damage level is more concentrated, while the distribution range of the nuclear density becomes wider as the damage level increases. In a comprehensive view, the kernel density ranges from 0.397 to 55.634 for the lightly damaged samples, from 25.951 to 198.988 for the moderately damaged samples, and from 115.419 to 312.612 for the heavily damaged samples. As shown in Figure 10, each damage level has its main distribution range, and there are obvious crossover locations between the damage levels, which are roughly estimated to be 60 and 150. Therefore, this article adopts the following damage grading criteria for surface cracks: no damage when the crack kernel density value is 0; light damage when the value is 0–60; moderate damage when the value is 60–150; and severe damage when the value is greater than 150; as shown in Table 3. It should be noted that this is a set of empirical parameters, and different study areas can determine the grading criteria of surface cracks according to the actual situation when classifying the damage degree.

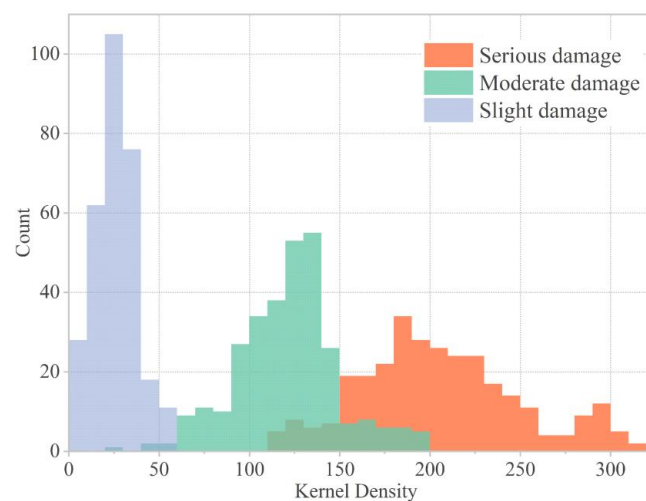


Figure 10. Comprehensive statistics of the crack density in the three damage level samples.

Table 3. Results of surface crack grading criteria.

	No Damage	Light Damage	Moderate Damage	Severe Damage
Crack kernel density	0	0–60	60–150	>150

3.4. Evaluation Results of Surface Cracks from UAV Images

Using the determined damage grading criteria, the surface damage areas in the study area were classified into three grades: light, moderate, and severe, as shown in Figure 11. The total surface damage area in the study area was 14,376.75 m², of which 72.77%, 23.22%, and 4.01% were light, moderate, and severe damage areas, respectively, which were mainly lightly damaged, while the distribution of severe damage areas was more scattered. The classification results show that the use of a 3 m bandwidth in the calculation of the crack kernel density can better demonstrate the damage of cracks in the study area, as well as avoiding an incorrect estimation of the damage extent.

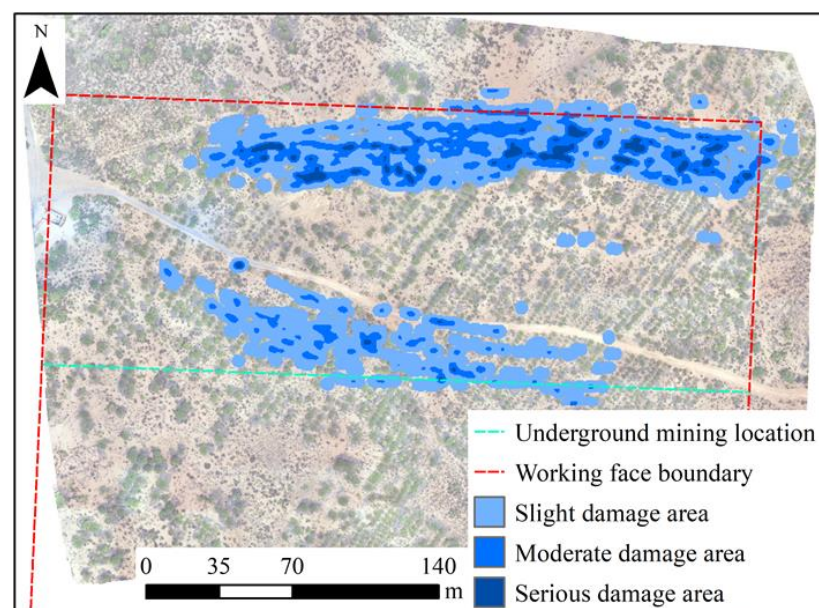


Figure 11. Grading results of the surface crack damage of each level of the grid.

Figure 10 shows that the crack-damaged areas in the study area are concentrated in two areas, and there is a 60–110 m wide almost no-crack area in the middle of the

two areas. The severity of surface crack damage in the northern area is much higher than that in the southern area, and the statistical analysis of the area of each damage level in the two areas shows that the area proportions of light, moderate, and severe damage areas in the northern area are 63.82%, 30.18%, and 5.99%, respectively, while the area proportions of light, moderate, and severe damage areas in the southern area are 88.83%, 10.71%, and 0.46%, respectively. The percentage of the surface area with a moderate and severe degree of damage is much higher in the northern area than in the southern area. Combined with the field survey results and crack extraction results, in the northern area, we found that the distribution of cracks is denser and the width of cracks is larger than those in the southern area. Therefore, according to the evaluation method of crack damage in this article, the surface damage in the northern area is more serious than that in the southern area.

We acquired high-resolution UAV imagery of the study area within a relatively short period after mining began on the underground workings, and against the underground coal mining data (Figure 11), the workings were mined from north to south and had advanced 130 m by the time the imagery was acquired. The crack damage areas obtained in this article are concentrated at the start of mining and the ongoing mining of the working face. According to the theory of mine subsidence, surface crack development advances steadily with underground coal mining, but the evaluation results of crack damage in this study area show that there is a large undamaged area in the middle of two crack-damaged areas. A field survey of the study area revealed that although surface cracks were developed in the above area, they were largely closed by subsequent mining and could not be extracted by high-resolution UAV images.

4. Discussion

Coal mining subsidence surface cracks are an important cause of surface ecological damage in mining areas, and the monitoring of surface cracks is the basic work to study the environmental changes and land reclamation decision-making in mining areas [2]. With the rapid development of UAV photogrammetry and remote sensing technology, rapid and large-scale monitoring of surface cracks in mining areas has become easy, and more and more research has been conducted for the extraction of surface cracks in mining areas based on UAV images [42–44]. However, the current utilization rate of surface crack information rapidly obtained by UAV photogrammetry and remote sensing is low, both for land damage studies in mining areas and for actual surface crack management work. The research in this article is a preliminary exploration attempting to use these surface crack monitoring data to analyze the surface crack damage in mining areas, and then apply the analysis results to the study of ecological changes in mining areas and the formulation of land reclamation decisions.

In this article, the crack nucleation density was used to characterize the degree of surface damage caused by cracks in coal mining subsidence sites in mining areas. Of course, the lattice density method is also a common method for calculating the density of feature elements, but the lattice density method has a certain degree of competent conjecture in the choice of lattice origin and lattice direction, and the different choices lead to some differences in the distribution of the crack density in the study area. There also is not a clear criterion for the selection of the grid size; too large or too small a grid size results in crack distribution characteristics not being reflected. The use of the kernel density method can effectively avoid the above problems, and we can determine a clear bandwidth criterion based on the extent of the impact of surface cracks on soil physicochemical properties and vegetation, which is a clear difference between this study and other types of geographic information analysis when using KDE. The 3 m bandwidth determined by the existing studies can avoid an incorrect estimation of the damage range of the surface crack and also fully take into account the fact that the impact of surface cracks on the surface has a certain range and decays with distance. However, the impact of cracks on the surface is multifaceted [45], extending beyond soil physicochemical properties and vegetation effects, and in further research, a comprehensive evaluation system can be constructed by

combining soil erosion, groundwater changes, and other factors to achieve the evaluation of the degree of ecological damage on the surface of coal mining subsidence areas in mining areas.

The study area of this article is a typical arid and semi-arid landscape, and studies in the same region have shown that surface cracks that develop after underground coal mining in arid and semi-arid areas are mainly divided into two categories: marginal surface cracks and dynamic surface cracks [46,47]. Marginal cracks usually appear at the edge of the mining subsidence basin in a “band” parallel to the working face boundary, with the crack width increasing and then stabilizing with mining activities, while dynamic cracks are located above the working face with the advancement of underground mining, and the crack width constantly changes with mining activities [46,47]. According to the above crack definitions, the cracks on the north side of this study area are edge cracks, while the south side has dynamic cracks. It has been shown that the dynamic crack width variation during underground mining in this area usually follows the law of “increasing and then decreasing” [47,48], especially since the study area in [47] is the same as that in the present study. This means that once the crack was developed at the beginning of the working face (northern area), it existed for a long time, while the dynamic crack inside the working face (southern area) had to go through a process of “automatic closure”, which led to more serious damage in the northern area than in the southern area in the evaluation results of crack damage in this article, and there is an undamaged area in the middle of the two areas. After underground coal mining in the wind-deposited sand area, the area with dynamic cracks on the surface had a strong self-healing ability, while the area with greater surface damage was the area with a marginal crack distribution [46,49,50], and surface crack management focused on marginal cracks.

Since a clear classification standard for surface crack damage has not yet been developed, this study provides a set of empirical parameters and determines a three-level classification: light, moderate, and severe damage, based on the results of field visits by experts in surface crack management in mining areas. It should be noted that the selection of damage samples for each class of cracks has a large impact on the damage evaluation results of surface cracks, so a comprehensive understanding of the development of surface cracks in the study area is needed, and then samples with significant differences in the density of the three types of cracks can be determined. Although this article obtained more satisfactory grading results of surface crack damage in coal mining subsidence areas, there is still uncertainty in determining the ground grading criteria artificially, although the grading accuracy can be improved by increasing the number of samples. At the same time, the surface crack grading criteria selected in this article are only used as empirical parameters for this study area, and the grading criteria applicable to a wider area require further in-depth study.

5. Conclusions

This article proposed a surface crack damage evaluation method based on kernel density estimation for UAV images, which entails quickly extracting coal mining subsidence surface cracks in mining areas from UAV high-resolution visible images, analyzing the surface crack damage in the study area using the kernel density estimation method using the crack density index as a grading index, and combining the field survey results of crack management experts to classify the damage degree of the study area into three levels: light, moderate, and severe damage. The following conclusions can be drawn.

(1) Crack extraction through image cutting and then stitching the crack extraction results is an effective method to avoid vegetation from interfering with crack extraction results, and the accuracy can reach 0.89.

(2) According to the existing research on the effect of surface cracks on soil physico-chemical properties and vegetation, the estimated bandwidth of the crack kernel density was 3 m. The maximum density value of the kernel density estimation was 316.956, and the surface damage area was 14376.75 m² due to the development of surface cracks.

(3) Statistical analysis of the kernel density distribution of the three damage-grade samples selected in the field survey conducted by the crack management experts (light: 0.397–55.634; moderate: 25.951–198.988; severe: 115.419–312.612) was carried out to determine the damage grading criteria for surface cracks in the study area (light: 0–60; moderate: 60–150; severe: > 150).

(4) The damage evaluation results show that the percentages of light, moderate, and severe surface damage in the study area were 72.77%, 23.22%, and 4.01%, respectively, which is a more satisfactory evaluation result of the damage level of a coal mining subsidence area.

The quick, convenient, and high-precision acquisition of information on the features of surface cracks in mining areas and the scientific and reasonable evaluation of surface damage caused by cracks can provide data support for the design of mine land reclamation and treatment plans. However, there is still uncertainty in the artificial determination of grading standards, which requires further in-depth research. The development of different treatment measures for different levels of damage caused by surface cracks also requires further discussion and analysis.

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