A Sphalt Crack Recognition Algorithm Based on Fuzzy Automatic Threshold C-Means Clustering Algorithm

Guoxun Zheng[1,2,3] and Zhengang Jiang[1,*]

[1] school of Computer Science and Technology, Changchun University of Science and Technology, Changchun, 130022, China

[2] school of Computer Technology and Engineering, Changchun Institute of Technology, Changchun, 130012, China

[3] Jilin Provincial Key Laboratory of Changbai Historical Culture and VR Reconstruction Technology, Changchun Institute of Technology, Changchun, 130012, China

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[1]School of Computer Science and Technology, Changchun University of Science and Technology, Changchun, 130022, China

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[3]Jilin Provincial Key Laboratory of Changbai Historical Culture and VR Reconstruction Technology, Changchun Institute of Technology, Changchun, 130012, China

ABSTRACT

Cracks are the most significant type of pavement disease, and the precise segmentation of cracks serves as an important decision-making basis for national preventive road maintenance management. In response to the problem of crack segmentation accuracy of existing pavement models under complex backgrounds, a crack recognition algorithm for remote sensing images based on the Fuzzy Automatic Threshold C-Means Clustering Algorithm (FATCM) was designed by incorporating local spatial and gray-level information constraints. The FATCM method can strengthen the inherent effectiveness of the traditional fuzzy C-means (FCM) algorithm, achieve uniform segmentation through fuzzy membership calculation and iterative process, and effectively eliminate edge ambiguity. The core innovation of FATCM resides in the introduction of the fuzzy local similarity measure, which is predicated upon the pixel spatial attraction model. This novel measure is astutely applied to automatically strike a refined equilibrium. Specifically, it ensures a high degree of insensitivity to noise, a factor of paramount importance in safeguarding the integrity of image data. Simultaneously, it minimizes the manifestation of edge-blurring artifacts, thereby proficiently retaining the minute and crucial details of the image. Multiple types of images in the Crack500 dataset were used in the experiments to evaluate the performance of FATCM. The experimental results show that this method has good detection results and can effectively extract weakly contrasted cracks and small cracks.

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1 Introduction

Asphalt concrete pavement serves as a frequently utilized road material. However, as time elapses and traffic load escalates, asphalt concrete pavement is susceptible to the formation of cracks [1]. These cracks not only have an impact on the visual appearance and driving comfort of the road but might also

*Correspondence: Zhengang Jiang (jiangzhengang@cust.edu.cn).

give rise to subsequent damage and potential safety risks. Consequently, the prompt identification and restoration of cracks in asphalt concrete pavement is of great significance. Asphalt concrete pavement is widely used in road construction due to its durability and smooth surface [2]. However, over time and with increasing traffic loads, it becomes susceptible to cracking. Hence, the prompt detection and mending of cracks in asphalt concrete pavement are of essential importance [3].

At present, there are many ways to identify pavement cracks. It can be divided into the crack identification method based on edge detection and the method based on neural networks. The crack recognition algorithm is based on network and convolutional neural networks [4,5], local average value standard deviation algorithm, multistage denoising algorithm, multi-feature fusion algorithm morphological method, and other crack identification methods in other fields of study [6,7]. It should be noted that the edge detection algorithm is sensitive to noise due to its low identification accuracy, while the asphalt pavement crack image has strong specificity because this application is gradually reduced [8]. Asphalt pavement crack recognition is based on neural networks, and most algorithms require a large number of data sets as data support. However, the time spent to realize the training of the neural networks is more redundant long, so there are fewer applications at this stage [9,10].

In practical engineering applications, efficient pavement defect detection is a necessary condition for ensuring traffic safety [11–13]. In most general-purpose object size measurement systems, the object is identified as a bounding box with its size represented by the width and height of the box [14]. Some methods ignore the conversion of pixel values to actual values and report the number of pixels as the final crack length [15,16]. This may be sufficient for applications in which the analysis of the shape of the crack is more important than its actual length. Similarly, in some cases, the relative pixel value of the object size may be of more interest than its actual value [17,18].

In recent times, due to the ceaseless upgrading and swift progression of image processing technology, certain scholars have put forward image enhancement algorithms. These algorithms aim to eradicate noise in crack images and accentuate crack features, thereby alleviating the complexity of crack segmentation. For instance, Zhang et al. introduced an image enhancement algorithm founded on the Automatic ridge transform. The findings suggest that this particular method can remarkably augment the overall and local contrast of road crack images [19]. Vivekananthan et al. Employed the gray discriminant approach for image preprocessing, utilized the Otsu algorithm to set thresholds, and applied the Sobel filter to detect cracks at the edges of image pixels [20]. Li et al. presented an inventive vision-based road crack detection strategy [21]. In this paper, a crack recognition algorithm based on a fuzzy automatic threshold C-means clustering algorithm is proposed to solve the problem that existing pavement models have low crack segmentation accuracy under complex backgrounds, combined with local space and gray information constraints. The FATCM method can reduce edge ambiguity artifacts while generating uniform segmentation, thus enhancing the traditional fuzzy C-means algorithm. The principal innovation of FATCM lies in the utilization of a novel fuzzy local similarity assessment approach predicated on the pixel spatial attraction model. This approach adaptively computes the weight factor for the histogram segmentation threshold sans any experimentally set parameters. The weighting factor demonstrates a high degree of adaptability to the image content. Through the application of the new fuzzy local similarity, the equilibrium between noise insensitivity and the minimization of edge blurring artifacts for the preservation of image details is automatically attained.

2 Algorithm and Methodology

2.1 Classic FCM

FCM fuzzy clustering algorithm is a kind of least squares algorithm [22,23]. The iterative method is used to optimize the target, so as to obtain the accurate data partition method, whose loss function expression is:

$$J_m = \sum_{i=1}^{c} \sum u_{ik}^{m} ||x_k - v_i||^2 \tag{1}$$

where the data set of FCM is $X = \{x_1, x_2, \ldots x_n\}$, n represents the number of waiting for cluster data; c represents the cluster center number; the index m represents the degree to which the membership between fuzzy classes is adjusted. Gradually increasing m can improve the ambiguity of the whole function and reduce the number of members of data. FCM fuzzy clustering algorithm is in pursuit of the best J_m reduction. Partial derivation is available for Eq. (2).

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}, \forall i, i = 1, 2, \ldots, c \tag{2}$$

Based on Eq. (2), the cluster center moment matrix V can be obtained $V = \{v_1, v_2, \ldots v_c\}$, where each subset is a cluster based on the s feature class-center. The calculation expression of the fuzzy classification matrix is:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{||x_k - v_i||}{||x_k - v_j||} \right)^{2(m-1)}}, ||x_k - v_i|| > 0, \forall i, k \tag{3}$$

If $x_k = v_i$, then $u_{ik} = 1$, and if $j = i$, then $u_{ik} = 0$, where u must meet the following conditions.

$$\begin{cases} \sum_{i=0}^{c} u_{ik} = 1, 1 \leq k \leq n \\ 0 \leq u_{ik} \leq 1, 1 \leq i \leq c, 1 \leq k \leq n \end{cases} \tag{4}$$

FCM cluster center U is a matrix that can be randomly initialized and can be calculated from all sample data points by Eq. (2). This method assigns membership values to data points, indicating the degree to which each point belongs to a cluster. It minimizes an objective function that measures the distance between data points and cluster centroids, weighted by the membership values. Traditional FCM does not consider the spatial context of the data points, which can lead to poor performance in noisy environments or when dealing with spatially structured data.

2.2 Fuzzy Clustering with Spatial Constrains (FCM_S)

To address the limitations of FCM, spatial constraints are introduced. These constraints consider the spatial relationships among data points, enhancing the clustering process by leveraging the spatial continuity and structure of the data. It combines fuzzy clustering with possible clustering to handle noise and outliers more effectively. The objective function of FCM_S includes a spatial term that penalizes differences in membership values among neighboring pixels or data points [7]. The modified objective function is typically of the form:

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m ||x_i - v_k||^2 + \frac{\alpha}{N_R}\sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m \sum_{r \in N_i} ||x_r - v_k||^2 \tag{5}$$

where x_i represents the gray value of the ith pixel, v_k indicates the prototype value of the kth cluster, u_{ki} stands for the degree of fuzzy membership of x_i in the kth cluster, m is the weighting exponent for each fuzzy membership, N_R is its cardinality, N_i is the collection of neighborhood pixels within the window surrounding the ith pixel x_i, and pixel x_r is the neighborhood pixel that belongs to N_i.

Introduces a membership function that represents the degree of typicality of data points with respect to clusters, rather than their probability of belonging to clusters. This approach is more robust to noise and outliers. By integrating possibility concepts with spatial constraints, the clustering process can better handle heterogeneous and noisy data.

2.3 Adaptive Fuzzy Local Information C-Means Clustering

The parameter within FCM strikes a balance between the resistance to noise and the capacity to preserve image details, exerting a significant influence on the ultimate clustering outcome. When there is a lack of prior knowledge regarding the noise, its selection becomes a challenging task. In practical scenarios, it is typically determined through empirical means. Additionally, this parameter remains constant for all neighboring windows throughout the entire image, which might disregard local variations in gray levels or spatial information.

Furthermore, in the FCM situation, using a filtered image may lead to a loss of original image details. To overcome these limitations, FCM_S suggests a new fuzzy factor for measuring local similarity, which intends to remove noise while keeping image details. However, FCM_S is not good at recognizing boundary-like pixels, and important information such as regional boundaries or crack edges will be overly smooth.

This article [7] presents a new Adaptive Fuzzy Local Information C-Means (ADFLICM) clustering method for classifying remotely sensed imagery through integrating local spatial and gray level information constraints. The method of ADFLICM can enhance FCM to some extent, realize uniform segmentation, and reduce edge blur artifacts.

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m \left[||x_i - v_k||^2 + \frac{1}{N_R}\sum_{r \in N_i, r \notin i} (1 - S_{ir}) \, ||x_r - v_k||^2 \right] \tag{6}$$

3 FATCM

FCM mainly focuses on the local features of data points, while the FATCM algorithm enhances the spatial continuity recognition of cracks in image data by introducing spatial information. This improvement allows the algorithm to better deal with the continuity and shape characteristics of cracks.

The gray level histograms of the pavement background and crack target pixels are almost Gaussian distribution, so two Gaussian distribution functions can be quickly estimated by the histogram fitting method, and then the intersection of Gaussian functions is the image segmentation threshold T^*. The specific algorithm is as follows:

Step 1. Initialization and denoising.

FCM is carried out to acquire the ultimate fuzzy matrix $U = \{u_{ki}\}_{c\times N}$, which serves as the initial matrix for FATCM. The Gaussian filter is employed to conduct the denoising process.

Step 2. Expressing the Histogram distribution.

It is assumed that the background in the image approximates Gaussian distribution, which can be expressed by Eq. (7).

$$H_b(i) = a_b e^{\frac{-(i-u_b)^2}{2\sigma_b^2}} + E_b(i) \tag{7}$$

And crack histograms in the image approximate Gaussian distribution, which can be expressed by Eq. (8):

$$H_c(i) = a_c e^{\frac{-(i-u_c)^2}{2\sigma_b^2}} + E_c(i) \tag{8}$$

where $E_b(i)$ and $E_c(i)$ are random noise, then the histogram function of the image is the superposition of them.

$$\begin{cases} H(i) = H_b(i) + H_c(i) \\ = a_b e^{\frac{-(i-u_b)^2}{2\sigma_b^2}} + a_c e^{\frac{-(i-u_c)^2}{2\sigma_b^2}} + E(i) \\ E(i) = E_b(i) + E_c(i) \end{cases} \tag{9}$$

Step 3. Get the best estimate.

When the energy $\sum_{i=0}^{255} E(i)^2$ of decomposition residue $E(i)$ is minimum, the optimal estimate is obtained.

This is an extreme value search algorithm with six variables. With the refinement of the search step size, the amount of computation will increase sharply. Therefore, the six variables can be estimated by the parameter estimation method, and the variables can be transformed into a function of the threshold T, so as to solve the single variable. The threshold change step is 1, which reduces the amount of computation.

Step 4. Calculating optimal segmentation threshold T*.

Turn the sum of squares function into an absolute value function and establish the criterion function:

$$\begin{cases} f_1(T,i) = \widehat{a}_b e^{\frac{-(i-u_b)^2}{(2\sigma_b^2)}} \\ f_2(T,i) = \widehat{a}_c e^{\frac{-(i-u_c)^2}{(2\sigma_c^2)}} \end{cases} \tag{10}$$

Therefore, the following criterion function can be established:

$$f(T) = \sum_{i=0}^{255} |f_1(T,i) + f_2(T,i) - H(i)| \tag{11}$$

The gray value T^* when the criterion function $f(T)$ takes the minimum value is the optimal segmentation threshold:

$$T^* = \arg\left[\min_{0 \le t \le 255} f(T)\right] \tag{12}$$

Step 5. FATCM completes iteration.

Based on T^*, FATCM adds local spatial and gray level information to traditional FCM objective function for better smoothness and less edge blurring. The FATCM objective function is as follows:

$$J_m = \sum_{i=1}^{N}\sum_{k=1}^{c} u_{ki}^m \left[||x_i - v_k||^2 + \frac{1}{N_R} \sum_{r\in N_i, r\notin i} \left(1 - \frac{T^*}{255}\right) ||x_r - v_k||^2 \right] \tag{13}$$

In the iterative process of the FATCM algorithm, not only the similarity between data points is considered, but also the spatial proximity may be combined to make the clustering results more consistent with the actual crack distribution. The algorithm repetitively refines the membership matrix and the cluster center until a specific termination criterion is satisfied, for instance, attaining the maximum number of iterations or when the change in the cluster center is less than a specific threshold.

4 Experiments and Results

4.1 Database

In recent years, many scholars open source their own crack segmentation data sets and manually annotate them at pixel level. Considering the complexity of real-world application scenarios, a common semantically segmented crack data set usually needs to cover a very wide range of pavement scenarios, crack scales, and noise types. For the intact road scene, the background is clean the texture is smooth; The damaged pavement scene is often accompanied by potholes and raised rough surfaces. For the dirty road scene, a large number of stains such as oil stains are distributed, and there may be interference from other road garbage. At the same time, when shooting pavement crack data, there are often problems such as insufficient light, uneven light, and shadow caused by natural light projection. In addition, the morphology and structure of cracks are also complex and changeable. Crack500 is used in this study which captured concrete and asphalt pavement on Temple University's main campus, including lane lines, pothole damage, salt and pepper noise, and other strong interference problems.

4.2 Evaluation Index

The accuracy of the method with different dimension sizes was computed by means of the F1 score metric. The F1 score is a reliable and commonly employed metric for gauging the accuracy of a classification issue (crack *vs*. non-crack) [12]. Recall (R) is defined as the proportion of cracks that are correctly classified to the cracks in the ground truth image data set.

$$\mathrm{R} = \frac{T_P}{T_P + F_N} \tag{14}$$

Precision (P) represents the ratio of the correct detections to the overall number of detected cracks.

$$\mathrm{P} = \frac{T_P}{T_P + F_P} \tag{15}$$

F1 score is calculated using Eq.(16):

$$F_1 score = \frac{2 \times \mathrm{P} \times \mathrm{R}}{\mathrm{P} + \mathrm{R}} = \frac{2T_P}{2T_P + F_P + F_N} \quad (16)$$

4.3 Result and Discussion

In this research, a Fuzzy Automatic Threshold C-Means Clustering Algorithm was devised for detecting pavement cracks.

The principal phases of the approach are classified into the subsequent steps:

1—The Gaussian filter completes the denoising process, Gaussian filter is used for denoising, in which the choice of parameter value has an important effect on the denoising effect. The greater the parameter value, the more pronounced the smoothing effect of the filter, but it may lead to the loss of edge information. Usually, the choice of parameter value depends on the noise level of the image and the degree of detail retention required.

2—Expressing the Histogram distribution, a histogram is a graphical representation of the distribution of gray values of an image. In crack recognition, the histogram can help to determine the gray level distribution of crack and non-crack areas in the image, so as to provide a basis for selecting a suitable threshold value.

3—Get the best estimate, the six variables can be estimated by the parameter estimation method, and the variables can be transformed into a function of the threshold T, so as to solve the single variable. The threshold change step is 1, which reduces the amount of computation.

4—Calculating Optimal segmentation threshold T^*.

5—FATCM completes iteration.

The method could detect most types of pavement cracks (longitudinal cracking, transverse cracking, random angle crack, and composite cracking) and other pavement surface defects. This method is based on Histogram thresholding algorithms, and the Gaussian distribution parameters of the crack and the background are put into the fuzzy clustering algorithm to extract the crack. Fig. 1 shows the recognition effect of some typical pictures like longitudinal cracking, transverse cracking, random angle crack, and composite cracking.

The fuzzy clustering algorithm is prevalently applied in image segmentation. In such field, the data frequently possess fuzziness, uncertainty, and complexity. Within these application contexts, the fuzzy attributes and soft clustering capabilities of the fuzzy clustering algorithm constitute its principal strengths, eliminating the necessity for verification through ablation analysis. The amount of true/false positives/negatives was determined by comparing the method results with the manual labeling results of human experts. All results are shown in Table 1.

The validation power of the proposed method is compared with some crack detection algorithms [14,16] in Table 2.

Table 2 illustrates the predominance of the proposed algorithm in relation to the others. It should be noted that the validation outcomes of certain of these studies rely on boundary and pixel-level ground truth analyses, which are more accurate than the approach adopted in this study for creating the ground truth. Nevertheless, network-level pavement crack detection surveys chiefly concentrate on the existence of cracks, their lengths, and types. Hence, more sensitive metrics might not be essential for this purpose.

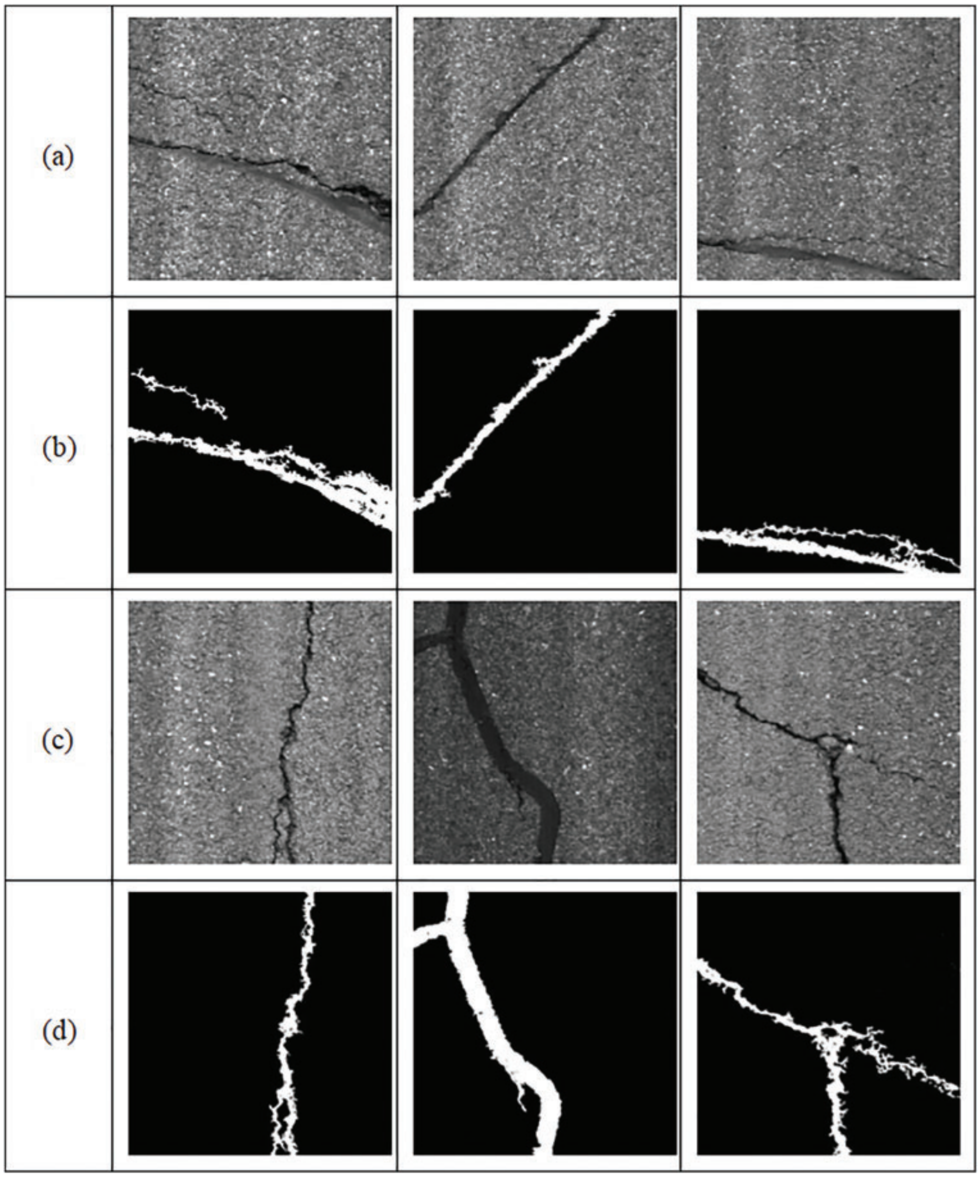

Figure 1: Shows the recognition effect of several typical pictures. (a) and (c) original images; (b) and (d) final output

Table 1: Validation results

Parameter	Number	Main indicator meaning
N	160	Total cracks
T_P	135	True positives (detected cracks that are real cracks)
F_P	24	False positives (detected cracks that are not real cracks)

(Continued)

Table 1 (continued)

Parameter	Number	Main indicator meaning
T_N	136	True negatives (undetected cracks that are not real cracks)
F_N	25	False negatives (undetected cracks that are real cracks)
P	0.84	The ratio of correct detections to the detected cracks
R	0.85	Capability of detecting all pertinent cracks within the data set
F1 score	0.84	The precision of classifying crack or non-crack

Table 2: Comparison of the validation results of the proposed method with some other methods

Method	Precision (P)	Recall (R)	F1 score
Canny	0.17	0.26	0.21
FCM	0.36	0.41	0.38
ADFLICM	0.68	0.79	0.73
CrackTree	0.71	0.77	0.74
CrackForest (KNN)	0.80	0.82	0.81
FATCM	0.84	0.85	0.84

The recognition of asphalt pavement crack images may be affected by lighting conditions and pavement environment, such as shadows, pavement signs, ruts, oil stains, etc. These factors may interfere with the accurate recognition of cracks. Meanwhile, the fuzzy clustering algorithm usually has a high time complexity and needs to perform iterative calculations, which will require a large amount of computation. To overcome these limitations, researchers may need to employ more sophisticated image preprocessing techniques, improve clustering algorithms to reduce reliance on initial conditions or develop new algorithms to improve the accuracy and robustness of crack identification. Single image recognition can be completed within 10 s. Due to the limitation of experimental conditions, more detailed comparisons and analyses are not carried out, and the recognition efficiency will be further improved in the next step.

In crack identification, noise and interference after clustering may lead to excessive segmentation or merging of cracks, which affects the accurate recognition of cracks. FATCM algorithm reduces the influence of noise and interference by adaptive threshold and spatial continuity processing. However, for very small cracks or cracks with a small gray difference from the background, the FATCM algorithm may still face challenges, and further image preprocessing or algorithm optimization is needed. The advantages of the FATCM algorithm in crack identification lie in its ability to process spatial continuity and noise, but there are also some limitations. Especially in dealing with small cracks and adjusting algorithm parameters. By combining with other image processing techniques, the accuracy and robustness of crack identification can be further improved.

5 Conclusion

Based on experimental results, the proposed Fuzzy Automatic Threshold C-Means Clustering Algorithm (FATCM) demonstrates significant advantages in crack detection across diverse image types. It consistently outperforms traditional methods, effectively detecting weak contrast cracks and small cracks even under complex background conditions. This is achieved through the innovative incorporation of a fuzzy local similarity measure and a pixel spatial attraction model, which collectively enhance the balance between edge detail preservation and segmentation homogeneity. By automatically determining weighting factors based on image content, FATCM eliminates the need for extensive parameter tuning, making it adaptable and user-friendly.

The innovations of FATCM lie in its ability to address two major limitations of traditional methods: (1) sensitivity to noise, which often leads to over-segmentation, and (2) loss of detail in high-noise or low-contrast regions. The proposed method achieves this balance by dynamically adapting to local gray-level and spatial variations, resulting in enhanced robustness and accuracy.

However, the method is not without limitations. One notable weakness is its computational complexity compared to simpler clustering methods, which may pose challenges for real-time processing in large-scale applications. Additionally, while FATCM performs well under diverse conditions, its sensitivity to extreme noise levels or highly heterogeneous regions requires further investigation to ensure universal applicability.

Despite these challenges, FATCM presents itself as a reliable and efficient solution for asphalt pavement condition assessment. Its capability to accurately detect intricate crack patterns suggests its potential for wide-scale application in national preventive maintenance programs. Future work could focus on optimizing the computational efficiency of the algorithm and exploring hybrid approaches that integrate FATCM with deep learning models to further enhance performance and scalability.

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Availability of Data and Materials: The data that support the findings of this study are openly available in [Crack500 dataset] at https://github.com/pss2002/Crack500 (accessed on 15 December 2024).

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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