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Research Article

Research on Image Texture Feature Extraction Based on Digital Twin

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The purpose of image smoothing is to improve the visual effect of the image and improve the clarity of the image, so as to make the image more conducive to computer processing and various feature analysis. Because the current technology fails to smooth the preprocessed image, it leads to the extraction of image texture features. The anti-interference performance is weak. For this reason, an image texture feature extraction technology based on the digital twin is proposed. Similarity analysis is carried out through the internal structure of the image, and the image is smoothed by the semisupervised learning method. On the basis of optimizing the denoised image through digital twinning, detect target feature points in the original image, then remove the abnormal and split feature points, assign the direction of image texture feature points, and build a fuzzy back propagation neural network model. Image texture feature extraction technology is implemented. The experimental results show that, compared with the traditional method, the proposed technique has a strong identification of original image features, and has a strong consistency with original data, and has a strong ability to resist the influence of abnormal data, noise, or redundant feature points.

1. Introduction

As an important carrier of information transmission, the effective study of images is the key to information data processing [1, 2]. Image texture feature extraction, as a key technology in information data processing, often becomes a hot and difficult point in image information research. For image feature extraction [3], it greatly increases the complexity of image processing. Effective extraction of various features in the image, in which the quality of feature points, the base of the number, the location, and distribution of the feature points will directly affect whether the subsequent imaging and matching work can be carried out smoothly [4]. Therefore, before carrying out specific imaging work, it is essential to perform different texture feature extraction work for different types of images, and it is also the basis and premise for the effective implementation of all technical means, which is of great significance to imaging work [5].

How to accurately extract image texture features has become the focus of current research on image information. Tarsitano et al. [6] utilize automatic machine learning methods for image feature extraction and classification. The possibility of applying machine learning methods designed for one-dimensional problems to the task of galaxy image classification is explored. Algorithms for image classification typically rely on multiple costly steps to extract features from galaxy images by analyzing the light distribution of elliptical isoilluminance maps and gather information sequentially. Sequences obtained with this method exhibit well-defined characteristics. Sequences are then trained and classified using machine learning algorithms designed by the Modulos AutoML platform, and how they optimize the classification task. However, this method is not optimized by the digital twin, and the image edge retention ability is poor, resulting in a slow running speed of image texture feature extraction. Kumar et al. [7] proposed the application of tetrolet-based adaptive color and texture feature extraction in content-based image retrieval, and designed a content-based image retrieval system that utilizes all these original image features to achieve an efficient content-based image retrieval system.

Natural images contain fully overlapping information, so in this approach, relevant image features are evaluated from their respective components. The YCbCr color space is used for the feature extraction process because the overlap of the Y, Cb, and Cr color planes is minimal. However, this method is not optimized by digital twinning, and the filtering effect of image detail information is weak, resulting in a low image texture recognition rate. In order to solve the problems of the above methods, an image texture feature extraction technology based on the digital twin is proposed. Based on the above denoising of the image and the optimization of the denoised image through digital twinning, to realize the image texture feature extraction technology, it is necessary to detect the target feature points in the original image, and then eliminate the abnormal and split feature points, so as to improve the extraction efficiency, reduce the error rate, and facilitate the effective implementation of the subsequent process. Compared with the angular and gradient features of the original image, the image extreme value feature based on Gaussian function is more stable, which can ensure the simplicity and accuracy of image texture feature extraction. Detecting all features of the original image in the GSS scale space can effectively remove abnormal feature points. The innovation of this technology is to analyze the intrinsic structural similarity of the image and smooth the image. On the basis of optimizing the denoised image through digital twinning, target feature points in the original image are detected, and then abnormal and split feature points are eliminated, and the direction of image texture feature points is assigned to realize the research of image texture feature extraction technology based on digital twinning. The research shows that the designed technology has better performance.

2. Image Texture Feature Extraction Technology

There is no clear and unified definition of image texture features. It is generally understood as the spatial change and repetition of the image gray level, or repeated local patterns (texture primitives) and their arrangement rules in the image. Texture feature extraction refers to the process of extracting texture features through certain image processing technology, so as to obtain the quantitative or qualitative description of the texture. Therefore, texture feature extraction should include two aspects: image preprocessing and image digital twin optimization.

2.1. Image Preprocessing. In terms of image preprocessing, the existing feature extraction technology has been widely used in image denoising and has achieved a good denoising effect. However, for the threshold denoising method, although the obtained estimated wavelet coefficient has good continuity, when the wavelet coefficient is greater than the threshold, there will be a constant deviation between the wavelet coefficient and the estimated wavelet coefficient. It will affect the proximity between the reconstructed image signal and the actual signal, and the error of the reconstructed signal will increase [8]. Therefore, for the above problems, the wavelet threshold denoising method is optimized to obtain an improved wavelet threshold denoising method. The specific steps are described as follows:

Formula (1) is a new threshold function.

$$Q_I = \begin{cases} Q_i + \dfrac{2\alpha \times \lambda}{1 + \exp(x)}, & |Q_i| \geq \alpha, \\ \\ 0, & |Q_i| < \alpha. \end{cases} \tag{1}$$

In formula (1), Q_i represents the wavelet coefficient, $\exp(x)$ represents the threshold function, and α represents the wavelet reconstruction value, $\lambda = 0.5$. Wavelet reconstruction is carried out through the new threshold function to obtain the estimated signal, that is, the signal after past noise.

$$F(k) = \alpha + \frac{2\alpha \times \lambda}{1 + \exp(x)} \times Q_I. \tag{2}$$

In the process of image preprocessing, the data containing labels are often very scarce, and they also need to be processed manually. Generally, unlabeled data account for a large proportion. The image is smoothed and preprocessed mainly through digital twins. In the process of preprocessing, the target classification function needs to be optimized in time [9]. We analyze the association relationship of each datum x_i and y_j in the dataset and establish the association matrix a_s. When $i \neq j$, the following definition need to be set.

$$W_j = E_{XP}\left(\frac{\left(x_i - y_j\right)^2}{2 \times F(k)} - a_s\right). \tag{3}$$

In formula (3), E_{XP} represents a diagonal matrix. An iterative function is established to solve the optimal label set E. The specific expression is as follows:

$$E(t) = W_j + (1 - \alpha) \times \beta. \tag{4}$$

In formula (4), β represents the regularization parameter. The main purpose of establishing a tag set E is to complete the transmission of different tags, that is, the data with tags are transmitted to the data without tags. In the process of transmission, it is necessary to make regularization judgments under set constraints and to give new labels to the data to ensure the smooth transmission of labels under the condition of ensuring that the original data will not be lost.

The main reason for image smoothing preprocessing is to eliminate the noise in the image [10], and to further improve the image quality. At the same time, the image quality is further improved. For a given content image X, both images are images in RGB color space [11], which not only contain the same content features but at the same time, the spatial structure is also very similar. In order to obtain a more ideal feature extraction effect, it is necessary to convert the image into a gray image X_g. First, the gray image X_g is subjected to mean filtering [12], and all pixel values in the gray image are converted to obtain X_{result}. Then the calculation formula of pixel value conversion is

$$X_r = Int\left(\frac{X_g}{\theta \times X_f}\right). \tag{5}$$

In formula (5), Int represents the gray content image of smooth preprocessing for semi-supervised learning, X_g represents the gray image corresponding to the content image, X_f represents the filtered image of X_g, and θ represents the weight coefficient of X_f.

In the semi-supervised learning method, the association matrix is established through X_r, and the semi-supervised learning method is used to smooth and preprocess the image. Finally, the preprocessed image is obtained as follows:

$$Y_r = \left(I - S_i\right)^{-1} \times X_g. \tag{6}$$

In formula (6), S_i represents the weight coefficient of label data smoothing.

2.2. Digital Twin Optimization of Images. After the preprocessed image is obtained, the image to be optimized is assumed and defined as R. The purpose of optimization through digital twinning is to make the obtained output image similar to the input image R [13]; the edge and texture should be the same as the denoised image Q, and the optimized image should be output, defined as P. The digital twin technology is used to perceive the full element and full state digital information of image texture features [14], to optimize the full element and full state features of actual images, and to construct the digital twin image texture feature model in combination with the three-tier architecture design to realize the image texture feature information management [15]. The overall structure of the image texture feature model based on the digital twin is obtained, as shown in Figure 1.

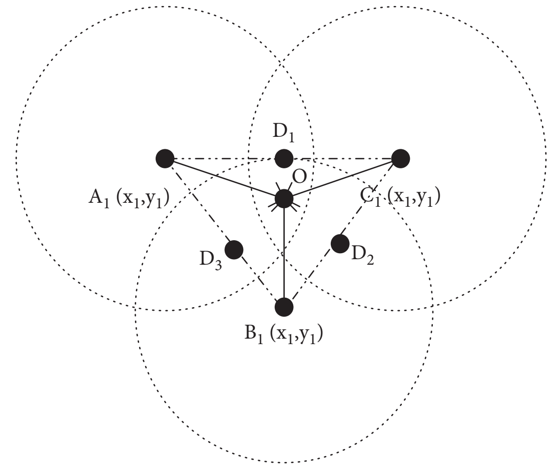

Figure 1: Image texture feature model based on the digital twin.

In Figure 1, O represents the central origin, $A_1\left(x_1, y_1\right)$, $B_1\left(x_1, y_1\right)$, and $C_1\left(x_1, y_1\right)$ represent the origin position of the change interval of the image feature threshold, while D_1, D_2, and D_3 represent intersections. According to the digital twin image texture feature model shown in Figure 1, data are extracted through threshold judgment analysis [16, 17]. We realize the functions of digital twin control, equipment monitoring, abnormal alarm, and life prediction, and determine the image texture feature model.

The image is assumed through digital twinning, and the local linear model is established by using the existing relationship between the denoised image Q_i and the filtered output image P_i, that is,

$$P_i = R \times P + a_k Q_i + b_k P_i. \tag{7}$$

In formula (7), a_k and b_k, respectively, represent windows centered on the pixel value k. The same gradient information exists between the denoised image Q and the output image P. The edge information of the denoised image can be effectively retained, which lays a foundation for image optimization and promotes basic morphological recognition in the image [18, 19]. The formula enables the output image P to retain the fuzzy information in the original image R to the greatest extent, which needs to be calculated by minimizing the cost function, that is,

$$M\left(a_k, b_k\right) = \sum_{i=w_k} \left(a_k Q_i + b_k - P_i\right). \tag{8}$$

In order to prevent overfitting, regularization parameters are set. If the value of a_k is too large, overfitting will occur, which will increase overall cost function, which can be expressed as $M\left(a_k, b_k\right)$. At this time, evaluating minimum cost function can effectively avoid overfitting. It can be seen from equation (8) that when the change of the fuzzy area is small, the value of a_k is close to 0. The filtering at this time is equivalent to a block filter, and the image is relatively smooth. When the fuzzy area changes greatly, the value of a_k is close to 1, which is more favorable for maintaining the edge information of the guide image. The effect of image optimization is mainly as follows: for the image optimized by the digital twin, the original depth of field value in the non-edge area is smooth, while the edge part is consistent with edge information.

3. Realize the Image Texture Feature Extraction Method Based on Digital Twins

The image texture feature structure and segmentation method assume that the texture is composed of precisely defined texture primitives. Because many textures violate this assumption, the application of this method is limited to a great extent. The specific contents of different stages of the method are shown in Figure 2.

It can be seen from Figure 2 that the different stage framework of the image texture feature extraction method is mainly completed by three steps. Step 1 and step 2 belong to the model training process, and step 3 is the recommendation process and visualization. In step 1, the input of the model needs to be determined first. This paper takes the characteristics of the image as the input, so as to build the

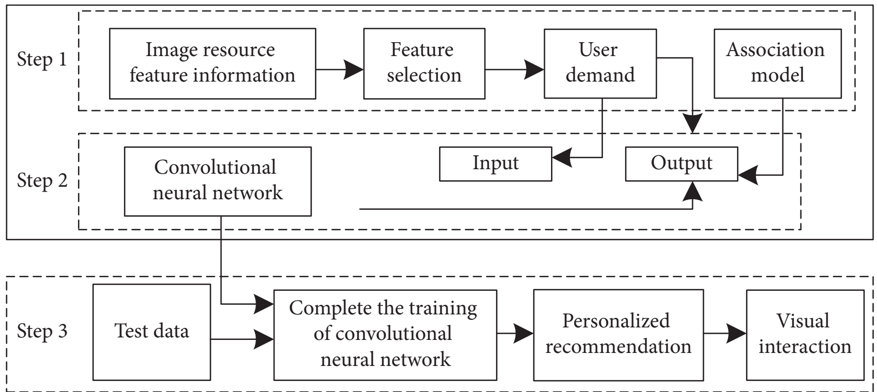

Figure 2: Structure diagram of different stages of the image texture feature extraction method.

correlation model between the user and the image, determine whether the image meets the needs of the user, and judge whether the image is recommended; Step 2 is to construct a convolutional neural network model according to the association between the user and the image, and complete the model training; Step 3 is to input the training data into the trained model to complete image texture feature extraction. Image texture feature point detection is to realize the algorithm design and obtain image features; the direction assignment process of image texture feature points is to realize the visualization of the results of image texture feature extraction technology based on the training process.

3.1. Image Texture Feature Point Detection. In the real image texture feature extraction space, the specific position of feature points can be captured reasonably and accurately through interpolation operation. Therefore, it is essential to perform subpixel interpolation on the GSS scale space. The interpolation method based on any function $f(x)$ is as follows:

$$f(x) = M(a_k, b_k) + \frac{\partial f^T}{\partial x}. \tag{9}$$

In formula (9), ∂f^T represents pixel interpolation, and ∂x represents the position vector of the extreme point offset. So far, the feature offset position value of the original image can be obtained. If the value is less than the established threshold, it can be determined that the feature point at this position is unstable and there is abnormal data, which will not be retained as the target feature point. In addition, because feature points at the edge of the image have too many influencing factors and are difficult to extract, it is necessary to set a threshold range first, retain the extreme points of these feature points at the edge within this range, and eliminate these feature points beyond the range to reduce the judgment error.

3.2. Image Texture Feature Point Direction Allocation. According to the above process, after the specific position recognition and detection of feature points, it is necessary to determine the distribution direction of feature points in advance to ensure that there will be no rotation or that it will not exceed the established range, so as not to affect the subsequent extraction of feature points at edges and inflection points.

When the feature point is at the center of the image, it is necessary to calculate the gradient distribution value of all feature points in all adjacent areas around it, and to take these target points in horizontal and vertical directions to calculate other feature positions in the same direction.

$$M_m(x_i, y_i) = \sqrt{\left[(x_i, y_i + 1) - (x_i, y_i - 1)\right]^2}. \tag{10}$$

In formula (10), x_i represents the position of the target feature point in horizontal direction and y_i represents the position of the target feature point in vertical direction. After a wide range of normalization processing, the specific description of the target feature point H can be obtained as follows:

$$H_m = \frac{h_m}{\sqrt{h_n^2}} + M_m(x_i, y_i). \tag{11}$$

In formula (11), h_m represents the size value of image features, and h_n^2 represents the similarity coefficient of image features. Based on this, the positional relationship between edge points and corner points is shown in Figure 3.

Based on the positional relationship in Figure 3, when the image is smoothed and preprocessed, the style attributes of the image are mined to obtain the similarity features of different image styles. The style similarity rules of various types of images are given below, namely,

3.2.1. Consistency Rules. In the same image, the image style is consistent, and there will be no two different image texture features.

3.2.2. Existence Rules. There is a certain similarity between the style of the image H_1 and the image, which can be converted into a similarity coefficient. They belong to the same or different texture features. There is a certain similarity between the styles of the image H_1 and the image H_2, which can be converted into a similarity coefficient. They belong to the same or different texture features. The value of

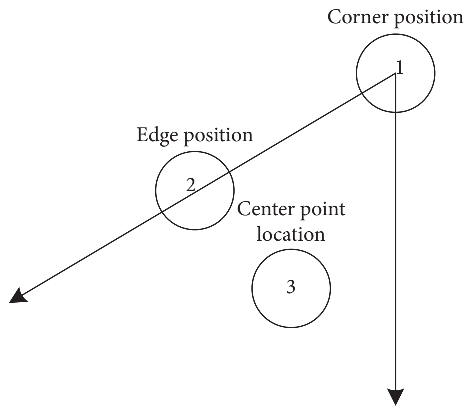

Figure 3: Distribution of center point, edge point, and corner point.

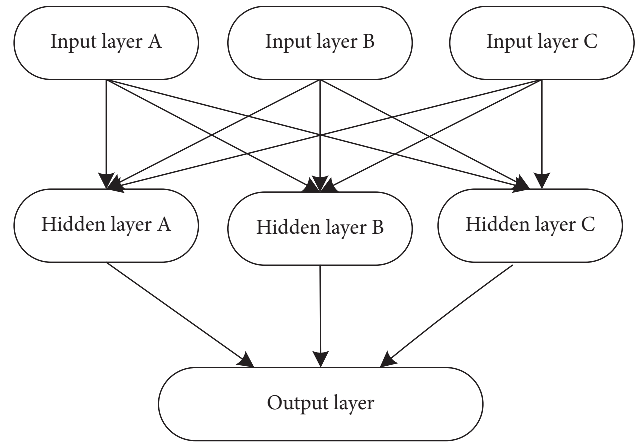

Figure 4: Fuzzy BP neural network model.

the similarity coefficient is in the $[0, 1]$ interval, where 0 represents no similarity and 1 stands for complete similarity. The setting symbol $R_{\text{simlirity}}$ represents the similarity of two images, namely,

$$K_\alpha = R_{\text{simlirity}}(H_1, H_2). \tag{12}$$

3.2.3. Comparable Rules. The image similarity coefficient of the same category style should be higher than the similarity coefficient. The following measures the characteristic distance function. The specific judgment basis is as follows:

$$\begin{cases} L_{\text{label}}(H_1) = L_{\text{label}}(H_2) \\ L_{\text{label}}(H_1) \neq L_{\text{label}}(H_2) \end{cases} \Rightarrow \begin{cases} R_{\text{simlarity}}(H_1, H_2) > R_{\text{simlarity}}(H_1, H_3), \\ \Updownarrow, \\ V_{\text{distance}}(H_1, H_2) < V_{\text{distance}}(H_1, H_3). \end{cases} \tag{13}$$

The similarity between the matrix vector and the matrix vector group is calculated by a formula, which is a very common concept. The distance function is mainly used to measure the similarity between matrix vectors and to count the similarity relationship between matrix vectors. The main purpose of image style recognition is to calculate the distance between the vector and the point group. When the distance between them is smaller, it indicates that each matrix vector has high similarity [20]. Through the above rules, assuming that the distance between matrix vectors is lower than any threshold, the vector can be divided into the nearest point group, that is, a category.

3.3. Implementation of Image Texture Feature Extraction Technology. The texture feature extraction of the image is realized, and the fuzzy BP neural network model is established, as shown in Figure 4.

According to the fuzzy BP neural network model shown in Figure 4, the type of input data is analyzed. Because the input data is an image type, the image information is not easy to quantify, and most of it is fuzzy data, so it is necessary to introduce fuzzy sets to process the data, mainly through the analysis and calculation of image data through membership functions, which can divide image information. It is divided into three levels: high, medium, and low, which are used as the three nodes of the input layer. Image information is input through the input layer of the neural network, and the corresponding training and extraction are carried out. When calculating the image information, the fuzzy set is introduced. As the input data of the input layer, each input point needs to be given a corresponding weighting operator, and the value range is within $[0, 1]$. The fuzzy weighting operator is composed of a fuzzy feature membership degree and a feature matrix, which is defined as B, and the composition of the fuzzy weighting operator is specifically defined as $B = \{b_1, b_2, b_3\}$,

$$B_1 = \frac{b_1}{b_1 + b_2 + b_3} \times A_1, \tag{14}$$

$$B_2 = \frac{b_2}{b_1 + b_2 + b_3} \times A_2, \tag{15}$$

$$B_3 = \frac{b_3}{b_1 + b_2 + b_3} \times A_3. \tag{16}$$

In formulas (14)–(16), the normalized fuzzy feature membership of the image is expressed as B_1, B_2, and B_3, and the corresponding feature matrix is expressed as A_1, A_2, and A_3. The image texture feature membership is calculated, the membership degree of image texture features is calculated, and the feature matrix corresponding to the image is judged through the feature discriminant. When the matrix meets the conditions, it is proved that the matrix has this feature, and the judgment and recording are carried out successively until all of the image texture features are extracted. Finally, the recorded values of features are expressed as b_1, b_2, and b_3.

The main function of the hidden layer is to combine the three results corresponding to the above three nodes, because only one result is needed in the final output layer. In order to solve this problem, the concept of correlation between points is used for combination.

We set the final obtained vector as K, and the corresponding vectors of the three nodes relative to the hidden

Table 1: Description of scale interval division.

Name	Source	Data quantity/Piece	Feature category
Characteristic point 1	Scale interval 1	1000	10
Characteristic point 2	Scale interval 2	1000	10
Characteristic point 3	Scale interval 3	1000	10
Characteristic point 4	Scale interval 4	1000	10
Characteristic point 5	Scale interval 5	1000	10
...	...	—	—
Characteristic point n	Scale interval n	—	—

Table 2: Experimental equipment and parameters.

Entry name	Specific parameters
Computer version and model	ASUSx550
Image NetDataset version	3.0.3
CPU	Intel i7-9700K
Memory	516 GB
Operating system	Windows10
Hard disk capacity	120 GB
Data sampling frequency	Collect data every 3 seconds

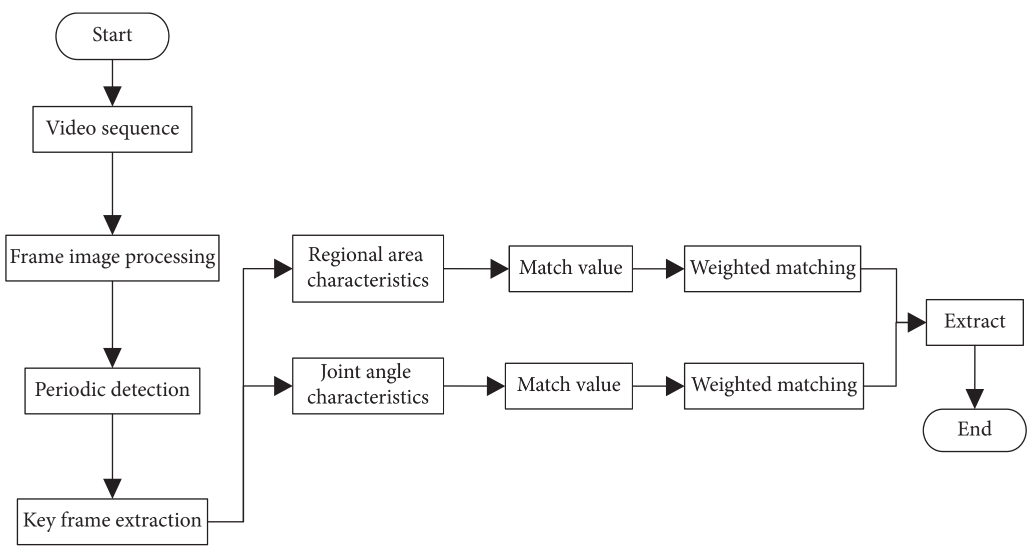

Figure 5: Flow chart of image texture feature extraction.

layer are expressed as C_1, C_2, and C_3. The corresponding mean square deviation calculation formula is

$$C^2 = (C - C_1)^2 + (C - C_2)^2 + (C - C_3)^2. \tag{17}$$

c_1, c_2, and c_3 obtained through formula (17) will be normalized. The three results are normalized to obtain an output result, that is, the extraction result of the feature matrix, so as to complete the research on image texture feature extraction technology based on digital twins.

4. Experimental Analysis

4.1. Experimental Environment. In order to analyze the feasibility of image texture feature extraction technology based on digital twins, experiments were designed to verify it. The experiment adopts the quick bird feature database with the widest coverage and most types at present. The archived data increase rapidly and have a strong inclusion rate. It is one of the important references of image processing technology at this stage. The selected dataset is from one million audio cover images, the original tree image in the quick bird feature database is used as the test sample for texture feature extraction. The size of the original tree image is 512×512 pixels. In order to ensure the rationality and authenticity of the experiment, methods in reference [6] and reference [7] are compared with methods in this paper. The texture distribution of the image after feature extraction is analyzed, the stability and accuracy of feature extraction are determined, and the excellence of the final experimental effect is obtained. The experiment was divided into two different groups. One group accurately analyzed the extraction of tree texture features, and the other group

Figure 6: Original tree image.

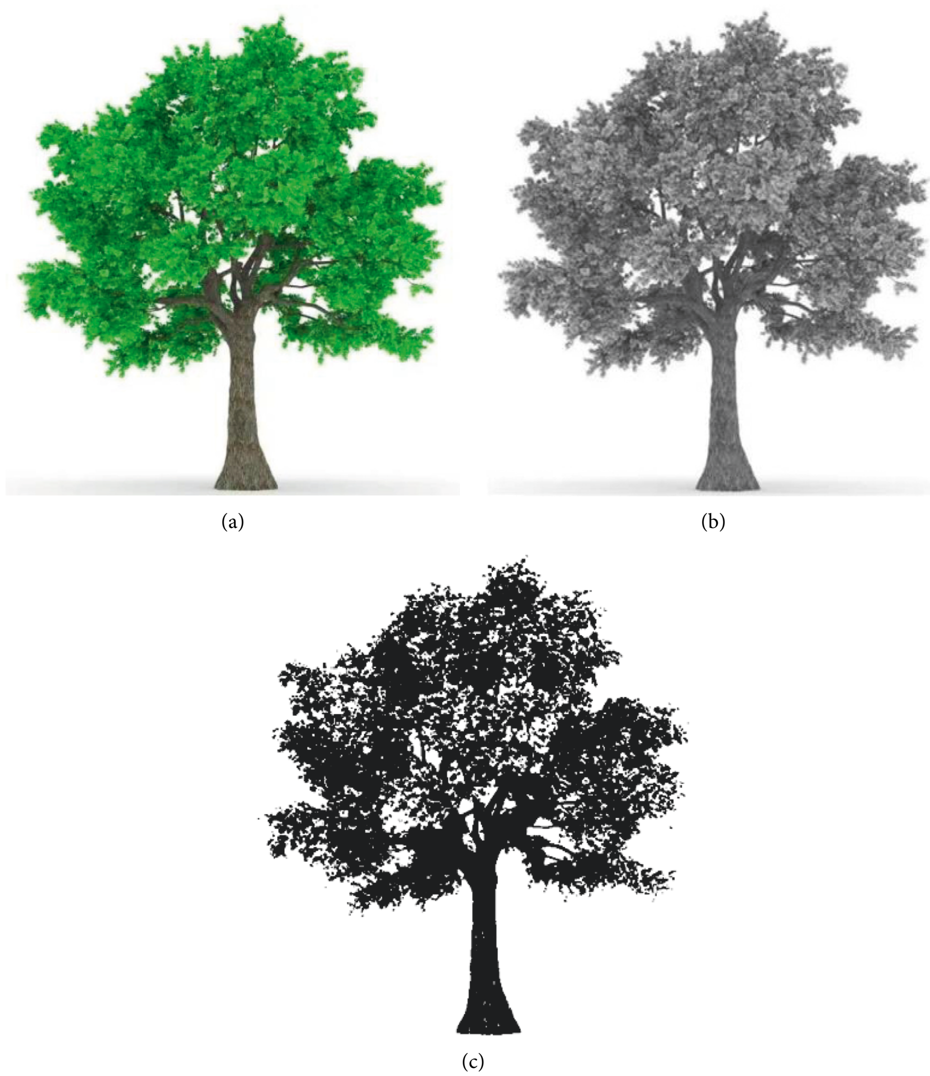

Figure 7: Tree texture feature extraction effects. (a) Paper method. (b) Reference [6] method. (c) Reference [7] method.

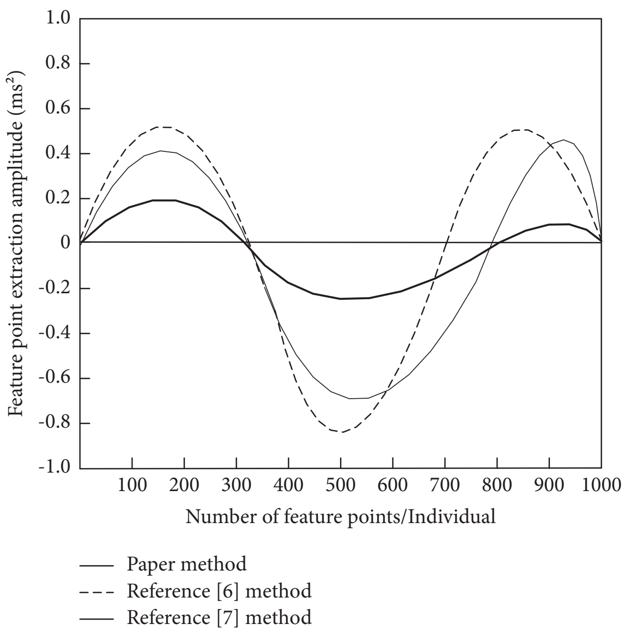

Figure 8: Amplitude change results of texture feature extraction of the three methods.

determined the specific loss time of each method through the extraction amplitude of feature points to ensure the comparability of experimental results. Using this method, the experimental data were divided into five different scale intervals to facilitate the feature extraction process. The division of scale intervals is shown in Table 1.

According to the description of scale interval division in Table 1, we set the experimental equipment and detailed parameters. The specific contents are shown in Table 2.

Based on scale interval division description in Table 1 and the experimental equipment and parameters in Table 2, the texture features of the original image were extracted. The specific extraction process is shown in Figure 5.

According to the extraction process in Figure 4, the texture features of the original tree image were extracted. In fact, the original image is shown in Figure 6.

By comparing the texture feature extraction effects of reference [6], reference [7], and this method on the original tree image, an effective conclusion was drawn. The results are shown in Figure 7.

As can be seen from Figure 7, the tree texture feature extraction effect of reference [6] and reference [7] is poor for this method, with low image saturation, blurred overall picture, and a weak sense of boundary. The main reason for this phenomenon is that the abnormal data of the original image were not processed accurately before the feature extraction process, which led to frequent noise in subsequent texture features and affected the experimental results. The overall flatness of the tree texture feature extraction image of our method is high, the capture effect of the tree texture details is good, the tree image is clear, saturation is high, the feature consistency with the original tree image is high, the global tone of the image is mild, and the visual viewing is the best, which shows that the experimental effect of the feature extraction method in this paper is excellent. It can effectively capture and extract the feature trend without noise or color distortion, and the overall performance is excellent.

By comparing the amplitude and time changes of feature point extraction, the experimental effects of different methods can be accurately analyzed. The variation results of texture feature extraction amplitude of the three methods are shown in Figure 8.

It can be seen from Figure 8 that the amplitude curve extracted from image texture feature points under the methods of reference [6] and reference [7] has been in a state of significant change, and the overall trend is unstable and has strong differences. In contrast, the amplitude curve extracted by this method for image texture feature points has been in a small amplitude fluctuation state, the difference between values is small and the stability is strong, the enhancement range between corresponding nodes is basically the same, and there is no turning point or inflection point, indicating that the feature extraction process of this method has a strong ability to slow down abnormal data. It can effectively remove abnormal data, accurately locate the correct data, and efficiently complete the extraction of target feature points.

To sum up, the image texture feature extraction technology based on the digital twin has a good extraction effect and superior performance.

5. Conclusion and Prospects

The digital twin-based image texture feature extraction technology filters and extracts image feature points. Its innovation is to analyze the intrinsic structural similarity of the image and smooth the image. Based on the optimization of the denoised image through digital twinning, target feature points in the original image are detected, abnormal and split feature points are then eliminated, and the direction of image texture feature points is assigned. It not only solves the problem of unclear feature extraction boundaries caused by noise and abnormal data, but also improves the difficult detection of feature points at edge positions. The experimental results are as follows:

(1) This method has an excellent effect on the surface texture feature extraction of the experimental sample tree.

(2) The designed image texture feature extraction technology based on the digital twin has clear image saturation and stable processing amplitude, which can realize efficient image feature extraction.

(3) Using the designed technology, image texture feature extraction is studied, and some results are obtained.

For texture images in some specific cases, there are still some deficiencies and areas that need to be improved and optimized, mainly as follows:

(1) The existing texture feature extraction methods cannot meet the requirements of practical application, and the classification accuracy is low, which can be further studied in the future.

(2) Most of texture images obtained in practical engineering are wrinkled and distorted textures, rather than having flat regularity, which makes the extraction of texture feature indexes a difficult problem; this can be discussed in depth in the following research.

Data Availability

Data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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