Analysis of Correlation Between Image Texture and Friction Coefficient of Materials

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Abstract—**It is unknown that whether friction coefficients of materials can be predicted by their images. In this paper, we explore the correlation between the image gray-level and the friction coefficient of materials. We introduce a systematic approach to find the correlation model. First, four key features were extracted from Gray-Level Co-occurrence Matrix (GLCM) using Hue Saturation Intensity (HSI) color space. Second, BP neural network was utilized to establish the correlation model between the image gray-level and the friction coefficient. The proposed approach was validated using a dataset with 100 samples. The results show that the average regression error of the model is 16.7% for the 100 samples, and 2.8% for the subset of 30 fabric samples among the totals. Within those fabric samples, the prediction error for new samples is 20.1%. The experimental results indicate a possibility of inferring the friction coefficient from the image of the material. This study might provide a way of automatically constructing a haptic database through the large amount of images on the internet.**

Keywords-haptic modeling; GLCM; feature extraction; neural network

I. INTRODUCTION

With the development of computer vision and the Internet, billions of images have been produced and become widespread on internet. To exploit the benefit of this big data, automatically synthesis and geometric modeling of virtual objects based on image data has become a hot topic in the field of computer graphics [1].

In the field of haptic synthesis, the physical properties of the object such as hardness, friction coefficients, texture details and other features are essential as the basic parameters to model a virtual object and calculate feedback force. The existing modeling methods are mainly based on two approaches: one is using the empirical parameters from the literature, and the other is through a measurement device to collect a user's movement and corresponding contact force data, and then calculate a fitting to estimate the physical parameters of the sample [2]. The drawback of the former approach is the lack of empirical data on theoretical parameters for objects with complex haptic properties, such as heterogeneous anisotropic objects. The latter has the advantage of being suitable for complex attribute characterization, but its disadvantage is that a special measurement system is necessary and a large amount of sample measurement experiments need to be carried out.

Compared to the large scale geometric models for graphic rendering, the database of haptic properties available in the literature for haptic rendering are rather small in both scale and data type. One representative example is the database developed by the University of Pennsylvania (UPenn) [3]. In this data base, 100 samples from ten categories with frictional coefficient and accelerations during a pen-sample sliding interaction are provided. Another example is the data set (with 43 samples) created by TUM group [4]. It's an open question that how to develop large scale haptic databases by using a simple way.

Based on the observation that image properties and haptic properties are two closely related attributes on the surface of an object, one may wonder whether it is possible to infer haptic properties of an object from its image. People can distinguish between different materials by observing their surface image, and different materials have their own haptic properties, so it may be possible to build a relationship between the surface image and haptic properties of the object. Once the relationship is constructed, we can leverage the existing massive resources of large-scale image data to propose a new method of haptic modeling, which will greatly simplify the work of constructing large-scale haptic databases. This possibility may produce broad application prospects such as e-shopping, e.g., by touching the physical properties of diverse cloth images on internet.

In this paper, we aim to explore the method of inferring the friction coefficients from the material image data and its prediction accuracy. To explore this problem, three steps are performed:

- The first is to construct a data set with collaborative visual-haptic attributes. The composition of the sample library should cover different types of materials, and have a certain amount of samples. As a preliminary study, we used the 100 material's image and the related friction coefficients from [3] for this research. The friction coefficients of the 100 materials was measured when a hemispherical metal tooltip slid on the materials. Section III.A briefly introduces the composition of the database.
- Second, select the appropriate image parameter and the appropriate haptic parameter as the paired parameters for the mapping. Considering there are many visual parameters of the surface, including color, gray, brightness, refractive index, etc.; In the haptic domain,

physical parameters of an object are also various, including hardness, friction coefficients, texture details and so on. The parameters should be chosen based on the intrinsic dependence of the constitutive relationship between the visual and haptic properties of the object's surface. In this paper, we choose gray gradient and friction coefficient as the mapping parameter pair, as both of them reflect the micro-geometric variability of an object's surface [5]. Section III.B and C provides a brief introduction to the theoretical basis for this parameter pair selection.

- The third step is to select the appropriate feature extraction method and feature classification method. In this paper, we choose the Gray-Level Co-occurrence Matrix (GLCM) to construct the feature, and form the eigenvector composed of four parameters. Furthermore we use the neural network method for feature classification. Section III.D provides the details of the feature extraction method and the feature classification method.

II. Related Work

Today's haptic technology has enabled people to feel the presence of virtual objects through various force feedback devices, such as Phantom [6], HapticMaster [7]. There are also technologies that allow people to feel the fine texture of the material, such as Poupyrev *et al.* designed a tactile feedback device TeslaTouch that generates electrovibration by using electro-static variations to allow the user to experience the texture's rough and uneven tactile sensation [8]. In order to simulate a more realistic feel of the material, it is necessary to establish a database of haptic textures in addition to force feedback devices. In this field, Kuchenbecker *et al.* has provided pioneering work with the Penn Haptic Texture Toolkit (HaTT), an open-source collection of contact force signals measured from 100 haptic textures which form a haptic database [3]. Schuwerk *et al.* establishes haptic texture database containing controlled and uncontrolled acceleration recordings for 43 different texture materials using a tool-mediated interface, which allows for analyzing feature candidates for texture recognition and retrieval systems [4].

In general, the sample of today's haptic databases is small, and there is lack of sufficient haptic contents for use in haptics research. In comparison, visual images of various materials in the Internet is numerous, and it has formed huge image databases [9]. One promising research direction is to explore an effective way of combining those massive images and existing small amount of haptic information, and thus to build a large scale haptic texture database that could be distributed on Internet. The potential results will drive the development of haptic field.

Many researchers have studied the mapping from texture image of material surface to haptic information. One early approach to modeling haptic texture concentrated on identifying the approximate friction coefficients of material surface by analyzing the pixels of a grayscale image on material surface to create a bump-map where height directly depends on shading value [10]. It is unclear whether there exists reliable correlation between surface height and pixel color or not. A second approach modeled texture force and friction force based on the height map which is established from the Gauss filter in frequency domain [11]. Further work has been done to employ 2D wavelet decomposition and wavelet energy signature in haptic data extraction, which confirm that techniques in computer vision could be replicated for computer haptics [12]. Furthermore, Mercier *et al.* [13] used luminance to compute the lacking height information necessary to generate the tactile force for haptic feedback. In summary, although those work obtain material's haptic information just from texture image, all of them adopted mathematical methods instead of using measured haptic data. As a result, haptic texture information rendered in this way were generally created as an approximation of what the surface might feel like, they couldn't quantify the realism compared to the measured data.

In this paper, we take a different approach of using measured dataset that consisting of both image and haptic data. Using the measured haptic data as a ground truth, we will be able to validate the mapping accuracy from grayscale image of an object to its friction coefficient.

III. METHODs

A. *Data Sources*

The purpose of this paper is to explore whether there is a relationship between the friction coefficient of the material and the related features of the material texture image, the data used are from data published by Katherine J. Kuchenbecker *et al.* [3]. They developed a set of haptic texture collection system, the force, acceleration and position information of the hand-held pen were measured when the pen slid on flat surfaces of 100 uniform materials, and through these raw data to calculate the friction coefficient and other tactile information, built a haptic database. Kuchenbecker *et al.* open up the data to promote the development of haptic areas, this paper will use their collection of 100 materials friction coefficient and texture image data, there are 48 kinds of fabrics, 30 types of paper, 22 kinds of metal, wood, plastic, carbon fiber, foam, stone, carpet, tile. Image acquisition equipment is a Sony D40 digital camera, the image resolution is 1024 x 1024, and the image is under same lighting conditions and related to the physical scale of the real material by 15 pixels / mm.

B. *Image Preprocessing*

The main purpose of image preprocessing is to eliminate irrelevant information in the image, enhance the detectability of the information and simplify the data to the maximum extent, thereby improving the feature extraction effect and improving the reliability of information identification. The image preprocessing method in this paper is color space conversion. Since the R, G and B components of the RGB color space are affected by light and the correlation of the three components is high, it is necessary to convert the image from the RGB space to the Hue Saturation Intensity (HSI) color space where the color and luminance information are independent of each other [14], only the intensity (I) value in the HSI color space is needed in the subsequent gray level co-occurrence matrix. The formula for converting from RGB color space to HSI color space is as follows:

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

where I is the intensity.

C. Gray-Level Co-occurrence Matrix

Because the texture is formed by the repeated distribution of the gray distribution in the spatial position, we use the gray-level co-occurrence matrix method to process the texture image and extract the texture feature. GLCM is an important texture analysis method based on estimating the probability density function of second-order combination condition of images, which was first proposed by Haralick in 1973 [15]. By calculating the gray relativity between two pixels in a certain distance and a certain direction in the image, all the pixels of the image are surveyed and statistic, which reflects the comprehensive information of the image in the direction, the adjacent interval, the change range and change speed. The mathematic expression of the co-occurrence matrix is:

$$P(i,j,d,\theta)=\{[(x,y),(x+\Delta x,y+\Delta y)]\,|\,f(x,y)=i,f(x+\Delta x,y+\Delta y)=j]\} \tag{2}$$

where x and y are the pixel coordinates in the image, i and j are the gray levels of the pixels, Δx and Δy are the positional offsets, θ is the direction which could be [0,45,90,135] degrees, d is the co-occurrence matrix step, as shown in Fig. 1.

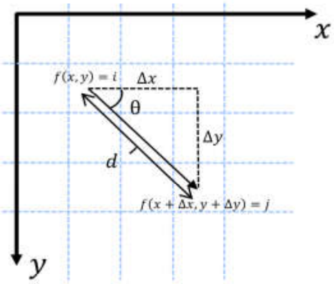

Figure 1. Pixel pair of Gray-Level Co-occurrence Matrix

For convenience of analysis, $P(i,j,d,\theta)$ is abbreviated as $P_d(i,j)$. When the positional relationship d between two pixels is selected, the GLCM is generated as follows:

$$\begin{bmatrix} P_d(0,0) & P_d(0,1) & \cdots & P_d(0,j) & \cdots & P_d(0,L-1) \\ P_d(1,0) & P_d(1,1) & \cdots & P_d(1,j) & \cdots & P_d(1,L-1) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_d(i,0) & P_d(i,1) & \cdots & P_d(i,j) & \cdots & P_d(i,L-1) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_d(L-1,0) & P_d(L-1,1) & \cdots & P_d(L-1,j) & \cdots & P_d(L-1,L-1) \end{bmatrix}$$

An element of the co-occurrence matrix represents the number of occurrences of a gray-level combination. The element $P_d(1,0)$ represents the number of occurrences of the case where the two pixel gradation levels of the positional relationship d are 1 and 0 on the image, and L is the number of gradation levels. The normalized co-occurrence matrix is obtained by dividing each element $P_d(i,j)$ by the sum of the elements to obtain a normalized value $\hat{P}_d(i,j)$ each of which is smaller than one. Haralick *et al.* defined 14 feature parameters of GLCM for texture analysis. It was found by Ulaby *et al.* that only four of the 14 texture features based on GLCM are uncorrelated. These four features are both easy to compute and give high classification precision [16]. Generally, four of the most common features are used to extract image texture features [17], as follows:

- Energy (Angular Second Moment(ASM)):

$$\text{ASM} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P_d^2(i,j) \tag{3}$$

The angular second moment is the sum of squares of the GLCM, and it is also called energy, which reflects the uniformity of gray distribution and the degree of texture. When ASM is large, the texture is coarse. On the contrary, when ASM is small, the texture is small.

- Contrast (CON):

$$\text{CON} = \sum_{n=0}^{L-1} n^2 \left\{ \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \hat{P}_d(i,j) \right\} \tag{4}$$

Contrast reflects the clarity of the image and the depth of the texture groove. The deeper the groove depth of texture, the greater the contrast is, and also smaller by contraries.

- Correlation (COR):

$$\text{COR} = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ij\,\hat{P}_d(i,j) - \mu_1\mu_2}{\sigma_1^2\sigma_2^2} \tag{5}$$

where μ_1, μ_2, σ_1 and σ_2 are defined as:

$$\mu_1 = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} \hat{P}_d(i,j)\,,\ \mu_2 = \sum_{i=0}^{L-1} j \sum_{j=0}^{L-1} \hat{P}_d(i,j) \tag{6}$$

$$\sigma_1^2 = \sum_{i=0}^{L-1} (i-\mu_1)^2 \sum_{j=0}^{L-1} \hat{P}_d(i,j)\,,\ \sigma_2^2 = \sum_{i=0}^{L-1} (j-\mu_2)^2 \sum_{j=0}^{L-1} \hat{P}_d(i,j) \tag{7}$$

The correlation is used to measure the similarity degree of the elements of the GLCM in row or column direction. When the values of the matrix elements are evenly equal, the correlation value is large; on the other hand, if the matrix pixel values differ greatly, the correlation value is small.

- Entropy (ENT):

$$\text{ENT} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \hat{P}_d(i,j) log\, \hat{P}_d(i,j) \tag{8}$$

Entropy is a measure of the information amount of an image, while it is in fact a measure of randomness. Entropy represents the degree of texture non-uniformity and complexity of the image. If the texture is complex, the entropy is large. On the contrary, if the gray level is uniform in the image, the entropy is small.

In order to observe the relationship between the friction coefficient and the image, we selected four materials from the fabric materials and get Fig. 2. Fig. 3 is grayscale height map of four material textures. It can be seen from Fig. 2 and Fig.3 that the greater the gap of four fabric texture image, and the non-uniformity degree is, the larger the friction coefficient is, but whether this relationship is universal or not is worthy of further exploration. To quantify this problem, this paper uses the GLCM to extract the features of image texture thickness, groove depth, etc. And we compare the features of different material textures with their friction coefficient.

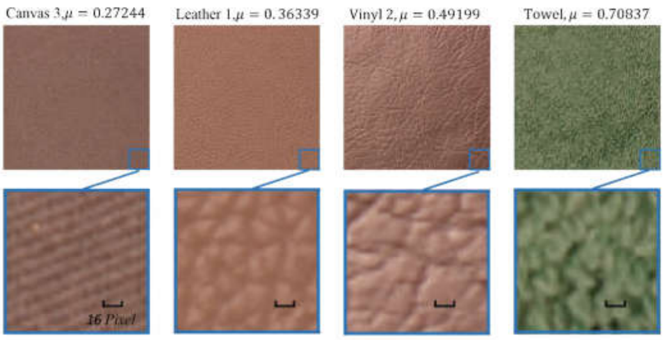

Figure 2. Four kinds of fabric materials texture image and theirs corresponding coefficient of friction (8 x magnification below).

Using four features calculated from four materials shown in Fig. 2 by GLCM method and theirs corresponding friction coefficient, we can draw Fig. 4. The following rules can be seen from Fig. 4: the larger the friction coefficient of the material, the larger the entropy mean and the second moment mean, the smaller the correlation mean and the contrast mean, but the correspondence is not strictly consistent. To investigate whether there is such a relationship between more materials, we research 100 kinds of materials' images and friction coefficients, and try to describe their relationship.

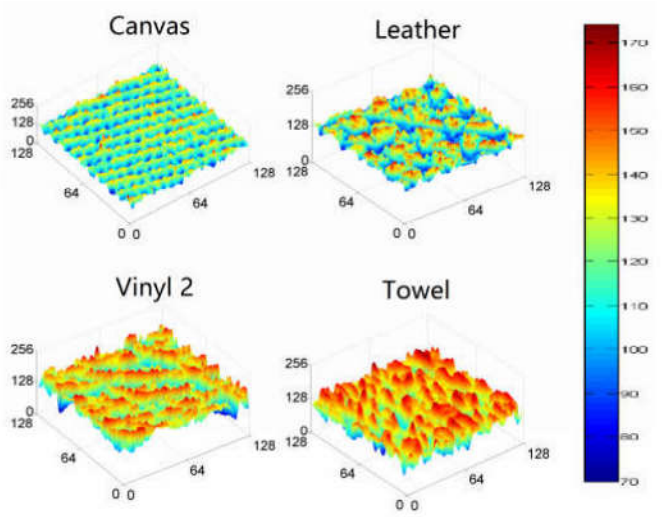

Figure 3. Grayscale height map of four materials. The unit of x and y axis is pixel, z is grayscale value.

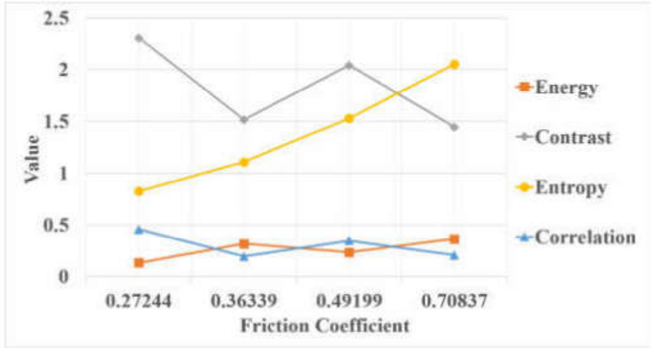

Figure 4. The relationship between friction coefficient and features value of four materials

D. BP Neural Network for Classification

After a preliminary study, we can find that the friction coefficient of material is not a simple linear relationship with each feature. To further explore this complex nonlinear relationship, we use BP neural network method. BP neural network is a typical supervised neural network classifier, the input and output of BP neural network is a highly non-linear mapping relationship, if the input node number is N, the number of output nodes is M, then the network is the mapping from N-dimensional European space to M-dimensional European space. When a pair of input and output modes are provided to the network, the neuron's activation function values will propagate from the input layer through the hidden layer to the output layer. In accordance with the principle of reducing error between the expected output and the actual output, the neural network will amend the connection weights layer by layer from the output layer through the hidden layer, and finally back to the input. By adjusting the weights of the BP neural network and the scale of the network, any nonlinear function can be approximated with any precision [18].

IV. TEST PROCEDURE

We use GLCM to get visual texture features of material images, put a certain number of materials' friction coefficients and their visual texture features as the training data to the BP neural network, and train a reliable neural network, then do prediction analysis based on the trained BP neural network. In the prediction analysis, we input new materials' image texture features to the trained BP neural network and then we get friction coefficients of the new materials as output which is the predicted value of the material's true friction coefficient. We compare the output value with the true value of friction coefficient, and then get correlation of those two data sets. The flow chart is shown in Fig. 5.

The feature vector of the image calculated by the gray level co-occurrence matrix contains four components, which are the energy, contrast, correlation and entropy of the GLCM, their meaning is shown in Section III.C. The 100 sets of material data is drawn out in Fig. 6.

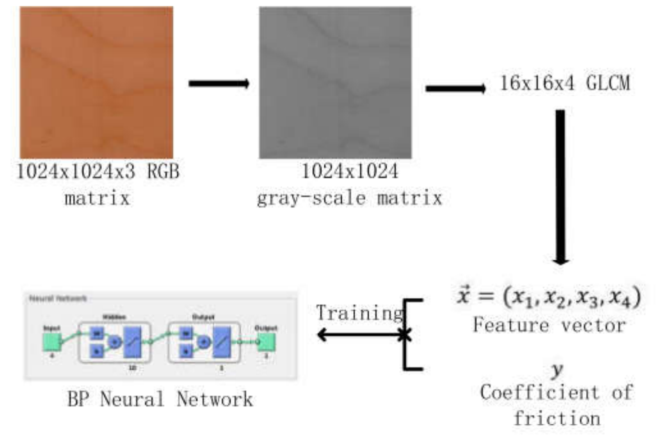

Figure 5. Flow chart of training the BP neural network

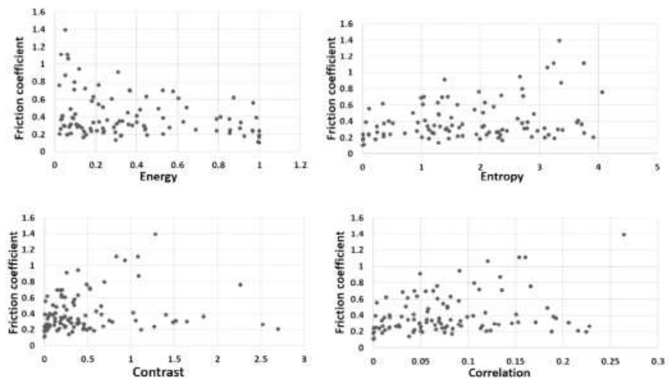

Figure 6. The distribution of friction coefficient and the feature components. The y-axis of each picture is coefficient of friction.

It can be seen from Fig.6 that the correlation between the texture feature and the friction coefficient is not obvious. We use the feature vector (x_1, x_2, x_3, x_4) as input and the friction coefficient μ as output to train the BP neural network. Each parameter is taken appropriate value according to empirical formula.

In order to observe the impact of material type on the training effect of BP neural network, we classify the material, use different type of materials as training data and random type of materials for comparison. The training results are shown in Table I, the relative error is used to describe difference between the inferred value of friction coefficient calculated by training neural network and the actual value of friction coefficient.

TABLE I. NEURAL NETWORK TRAINING RESULTS

Input sample data	100	30	22	30
The type of material	All	Fabric	Paper	Random
Neural network type	BP(10)	BP(3)	BP(3)	BP(3)
The relative error	45%	24.1%	26.7%	44%

Note: Using BP neural network, BP (n) means that the number of hidden layer parameters of neural network is n.

From the results in Table I, it can be seen that classification can effectively reduce the relative error, but the relative error is still very large. In order to further reduce the relative error and enhance the training effect, we use the method of self-expanding training data [18]. For example, we have N kinds of material training data sample $(x_1, x_2, \cdots, x_n)$, and then we expand the N sizes of the sample to 3N sizes of the sample like $(x_1, x_2, \cdots, x_n, x_1, x_2, \cdots, x_n, x_1, x_2, \cdots, x_n)$. Similarly, we can get 5N, 6N sizes of the sample, and then train them to get the result data in Table II.

TABLE II. RELATIVE ERROR AFTER TRAINING

Input sample data		100	30
The type of input material		All	Fabric
Neural network type		BP(10)	BP(3)
Sample data expansion factor	1X	45%	24.1%
	3X	23.1%	5.3%
	5X	18.6%	3.6%
	6X	14.9%	3.8%
	7X	16.7%	2.8%

Note: nX means that the sample is expanded to n times

From the data in Table II, it can be seen that the self-expanding method can effectively reduce the training error. It is noted that the training error of '7X' is higher than '6X', indicating that the neural network is overfitting. From the results in Table I and Table II, it can be seen that the training error of the neural network can be greatly reduced by the method of material classification and sample self-expansion. In addition, whether the functional relationship between the friction coefficient and the four texture features quantity can represent the real relationship depends on the prediction effect in the further experiment.

Figure 7. Friction Coefficient and Image of 30 Fabric Materials

As shown in Fig. 7, 30 kinds of fabric materials were randomly divided into two groups, of which 25 kinds of materials to do neural network training data, 5 kinds of materials to do prediction. We use 25 kinds of materials to train the BP neural network, and then take five kinds of material texture feature as input to the trained neural network, thus we get the inferred friction coefficient of five materials as output. Finally we calculate the relative error between the real value of the friction coefficient and the inferred value, the result is 20.1%. This preliminary result suggests that there is a correlation between the friction coefficient and the image texture.

The reason why the experiment is not ideal enough is probably that we lack sufficient samples of materials, which keep us away from observing the effective rule, and the image resolution is somewhat low to infer haptic properties. In the next step, we will try to expand the sample data volume and explore new features extraction method and better training classification method in the follow-up work.

V. CONCLUSION

In order to find out whether there is a relation between materials' texture image feature and friction coefficients, this paper first transforms the texture image into HSI color space and extracts the I component, next extracts the mean and variance of texture feature by using gray-level co-occurrence matrix, and then use the BP neural network to fit the relationship between four feature quantities and the friction coefficient. Finally, the correlation between the image feature and the friction coefficient is determined by BP neural network prediction precision.

In the process of experiment, we find the effect of material type on the accuracy of BP neural network, thereby we found that the material type has an effect on the relationship between the texture image feature and the friction coefficient, and a better fitting effect could be achieved by classifying materials. The final 20.1% prediction error of neural network indicates that there is a correlation between the texture image feature and the friction coefficient. It should be noted that the friction coefficients we used is between the 100 materials and a hemispherical metal tooltip, so the conclusion is only established in this case. In the future, we plan to improve the use of the gray level co-occurrence matrix method by performing more experiments to find better parameter settings of pixel gray level, step parameter values, etc.

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