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Random Forest in Image Segmentation

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Abstracts: Random forest algorithm has the advantages of fast processing speed in image processing, and can be used in image segmentation. The aim of this paper is to study image segmentation based on random forests. The principles of random forest algorithm and feature extraction are described in detail, and the characteristics of RGB colour space and HSV colour space are analysed. The experimental procedure for segmenting annual rings images is described. Regions of interest are extracted and then, based on the differences in colour and texture features of early and late wood, the segmentation of annual rings images is achieved. The experimental results show that the random forest algorithm achieves better results in image segmentation.

1. Introduction

With the increasing advancement of technology and computers, people nowadays rely more and more on computers to obtain all kinds of information and use computer technology to solve the various problems they encounter [1-2]. In the process of problem solving, how to process image information is a key research direction for scholars. Humans have a powerful visual processing system that facilitates the reception of information from the surrounding environment, but most information is image information, as receiving information from the outside world through the eyes is the easiest and most efficient way for humans. Digital images are displayed in the form of pixels and two-dimensional arrays, and are one of the ways in which image information is preserved in images [3]. The use of computer technology to process image information has become an accepted means of developing image engineering. Image segmentation is a part of image processing and is necessary to process the content of an image [4].

Digital images contain a very large amount of information, which is complex and abstract, and how to obtain useful information from them is a major concern of researchers [5]. Changman Son proposed an RF-based segmentation method for apple images. Firstly, texture features such as energy were extracted from the original image based on the grey scale co-generation matrix (GLCM). Secondly, the G+0.5 R-B and S+I colour components in HSI space were computed as combined colour features to prevent sky and brightly revealed regions from affecting the segmentation results. The extracted texture and colour resources were then combined into pixels. Finally, random forestry is applied to the mixed feature segmented images and the segmentation results are compared to traditional methods that only consider a single feature type. Extensive experimental results qualitatively and quantitatively demonstrate the advantages of their algorithm, with a significant improvement of 22.18% in segmentation accuracy compared to algorithms using only texture features [6]. Anamika Maurya proposed a new segmentation method called shape model guided random forestry (SMRF), to analyze MCE data. This method uses statistical shape model of myocardium to guide random forest (RF) segmentation in two ways. Compared with the classical RF and its variants, the segmentation accuracy has been significantly improved [7]. Mohamed Abdel-Basset targeted the problem that traditional semantic segmentation models cannot accurately describe object contours in complex environments, a segmentation block-based image semantic segmentation method was proposed. The structural forest method is used to generate contour probabilities. And the initial blocks of image segmentation are transformed using the watershed method. To avoid over-segmentation, the Ultra Distance Contour Map (UCM) algorithm is used to select the appropriate threshold to generate the segmentation blocks to obtain more accurate contour information [8]. Therefore, at this stage of the trend, the study of different neural networks to improve the effectiveness of image segmentation is not only beneficial for the development of the technique, but also helps to carry out practical applications.

This paper begins with background information on image segmentation, the current stage of development of segmentation techniques, and introduces the relevant knowledge points, and then describes in detail the random forest algorithm mentioned in this paper, and based on this, and the introduction of image texture features in the image segmentation process to enhance the effect of segmentation.

2. Research on the Application of Random Forest in Image Segmentation

2.1. Random Forests

Random forests belong to the category of integrated learning, and their construction process is roughly represented in Figure 1. Each tree is trained from a self-help sample set, and at each internal node, a random selection of attributes from all the input feature attributes is used for splitting, and these features are used to split in turn, and finally the best one is found to split the node based on the attribute metric, while the parameters of the weak learner at that node are saved for use in testing. The sample set is divided top-down and the sample data points reach the leaf node when the selected attributes cannot separate the sample set at the node, i.e. the sample set is considered to be of the same class.

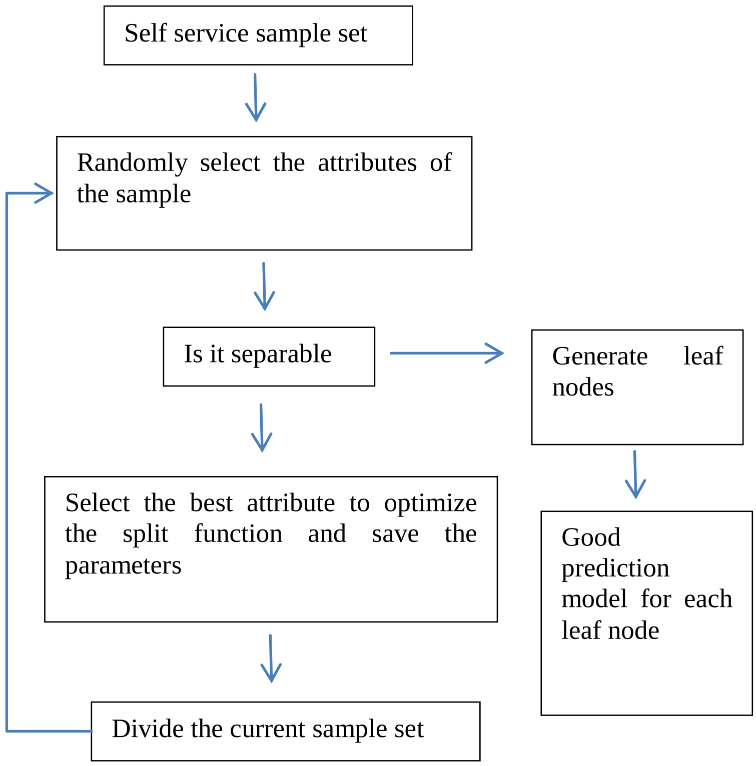

Figure 1. Construction process of random decision tree

2.2. Feature Extraction

(1) Colour features

Colour is the simplest and most effective feature of an image. The colour histogram is simple and insensitive to image size and rotation. Colour histograms and cumulative histograms are commonly used to represent the colour features of an image.

(2) Texture features

Texture is a common feature for content-based image retrieval, reflecting the relationship between the surface structure of an image and its surroundings. Three methods for describing texture are commonly used for image retrieval based on texture features: structural, statistical and spectral methods. Structural analysis methods are based on the structural features of an image; statistical methods calculate information about the spatial distribution of colour intensity in an image. Spectral methods use the Fourier transform and wavelet transform to convert an image from the spatial domain to the frequency domain.

2.3. Characteristics of Colour Space

(1) RGB colour space

The RGB colour space was originally designed to use red (Red), blue (Blue) and green (Green) as the base colours, which are combined into various colours throughout the colour space by varying the strength of the three base colours.

The RGB colour space was first used in colour televisions to display colour images through the luminous intensity of red, green and blue light-emitting materials and was later used extensively in computer monitors. However, this colour space has a number of drawbacks. Firstly, RGB is an uneven colour space, where the distance between two points and the difference in colour at the corresponding point do not match; secondly, the three components of RGB are not independent, and a considerable amount of image information is stored on each component; finally, the three components of RGB are based on colour without any pictorial significance.

(2) HSV colour space

The HSV colour space uses Hue, Saturation and Lightness (Value), and is very similar to the HSI colour space, with the model presenting an inverted circular vertebra. The H components of HSV and HSI have the same meaning, both indicating colour types, and their definitions and values are almost identical, with the H component of HSI indicating a change in wavelength, while the H component of HSV is artificially defined as red, green and blue corresponding to angles 0 °, 120 ° and 240 °respectively, with uniform colour variations in between. The S component of HSV reflects the intensity of the colour, which corresponds to the painter's method of colour matching, where a colour with 100% saturation is usually not 100% pure. The I of HSI is referred to as luminance, with the highest luminance reaching the intensity of white light, while the V component of HSV reflects the luminance, with The highest luminosity achieves the brightness of a medium grey. Therefore, the warmth, lightness and darkness of an image are controlled by both the S and V components of the HSV colour space.

3. A Survey and Study of the Application of Random Forests in Image Segmentation

3.1. Experimental Procedure

Forty samples of annual disc images, 1024 pixx 1024 pixel image resolution, 20 training samples and 20 test samples were collected for the experiment. 500 pixel points were randomly selected for each training sample. A total of nine colour features were selected from eight texture elements that deviated from the h ~ 3, H4 and σ, 0 norms, and normalised for the average energy, contrast and correlation of r, g, b, h, s.

The number of decision trees is an important parameter in the random classification of forests. In general, the larger the decision tree, the higher the classification quality and the longer the time used for learning and prediction. For the annual image data of the wheel trained in this paper, decision trees 200 - 800 were chosen to test the interval classification of decision tree 10.

3.2. Random Forest Classifier

In the experiments, the random forest was used as the classifier to vote and classify the multidimensional feature vectors collected in the preliminary stage, and the most voted category was the final classification result. The results are expressed as:

$$H(x) = \arg\max_{Y} \sum_{i=1}^{k} I(h_i(x) = Y) \tag{1}$$

where H(x) denotes the final output result, h(x)i denotes a single decision tree, I denotes the schematic function and Y denotes the output variable. The extracted feature vectors grow into random forest models after continuous splitting.

4. Analysis and Research on the Application of Random Forests in Image Segmentation

4.1. Random Forest Algorithm Segmentation

(1) Colour features

In the g channel of the RGB colour space, the grey values of the early material pixels are significantly higher than those of the later pixels. In the s channel of the HSV colour region, the pixels of the late material have much larger grey values than before, are more concentrated and are not disconnected.

(2) Texture feature selection

The contrast of an image can be interpreted as the sharpness of the image texture. The deeper the grooves in an image, the greater the contrast, which visually demonstrates the clarity of the image. The formula for calculating contrast is as follows:

$$f_1 = \sum_{n=0}^{L-1} n^2 \{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p^2{}_\delta(i,j)\} \tag{2}$$

Where: |i-j|=n. If the grey level is L, then Pδ is a square matrix of LxL, where Pδ (I, J), (I, J = 0, 1, 2... .L-1) is defined as the probability δ = (Dx, Dy) of two pixels with grey levels I and J at spatial locations. Entropy is a measure of the amount of information in an image. The more detailed the image texture, the greater the entropy value. The entropy is calculated as follows:

$$f_4 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \hat{p}_\delta(i,j)\log\hat{p}_\delta(i,j) \tag{3}$$

Table 1 shows the texture features of the feature window and it can be seen that there is some variation in the texture features, as shown in Figure 2.

Table 1. Texture characteristics of early wood and late wood (a feature window)

Texture features	Contrast mean	Correlation mean	Energy mean	Entropy mean
Early wood	0.56	0.22	0.05	2.14
Latewood	0.65	0.14	0.15	1.87
bark	2.65	0.02	0.02	3.68

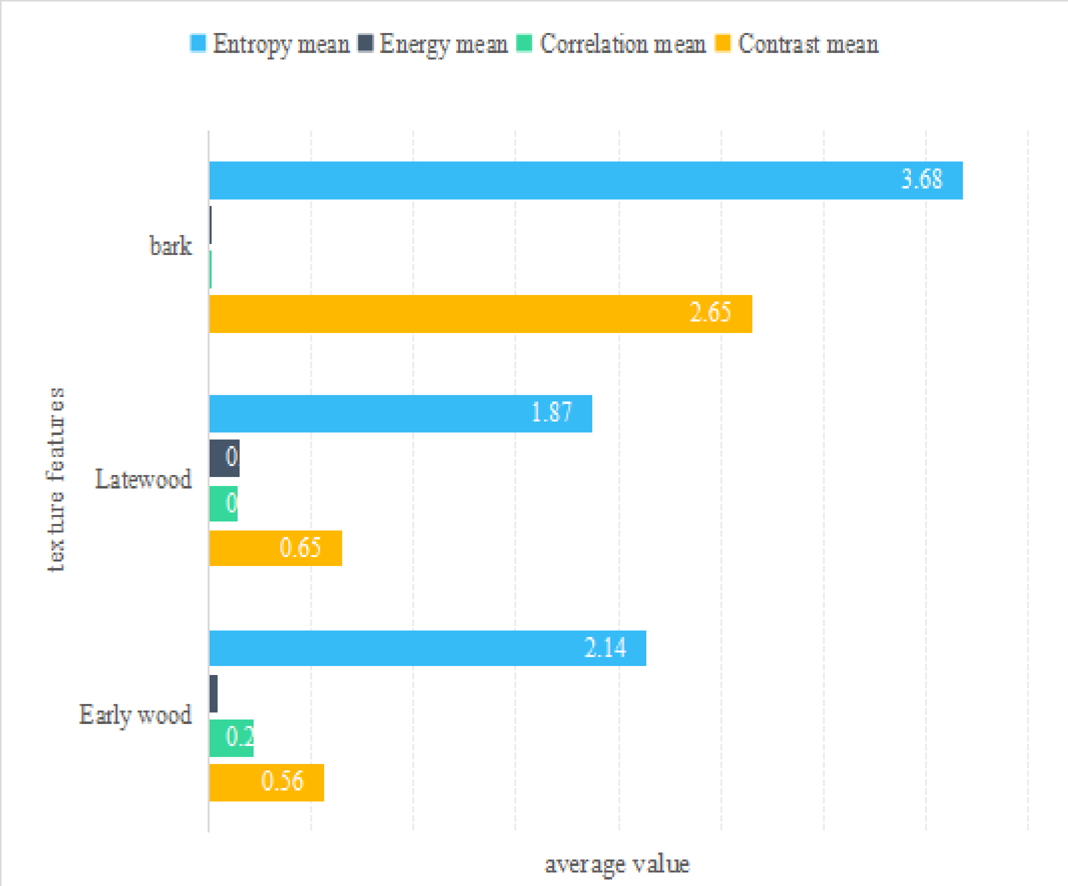

Figure 2. Average value of wood image texture features

4.2. Analysis of Segmentation Results

The RF algorithm segmented the annual wheel images with a pixel accuracy of 0.95, an average pixel accuracy of 0.89, an average region overlap of 0.87, and a frequency weight intersection ratio of 0.9, as shown in Figure 3.

Table 2. Segmentation effect based on random forest algorithm

Picture No	Pixel precision (PA)	Average pixel precision (MPA)	Average area coincidence (M-IoU)	Frequency weight cross merger ratio (FWloU)
1	0.92	0.90	0.88	0.91
2	0.98	0.92	0.91	0.93
3	0.93	0.85	0.86	0.86
4	0.97	0.88	0.89	0.88
Average	0.95	0.89	0.87	0.90

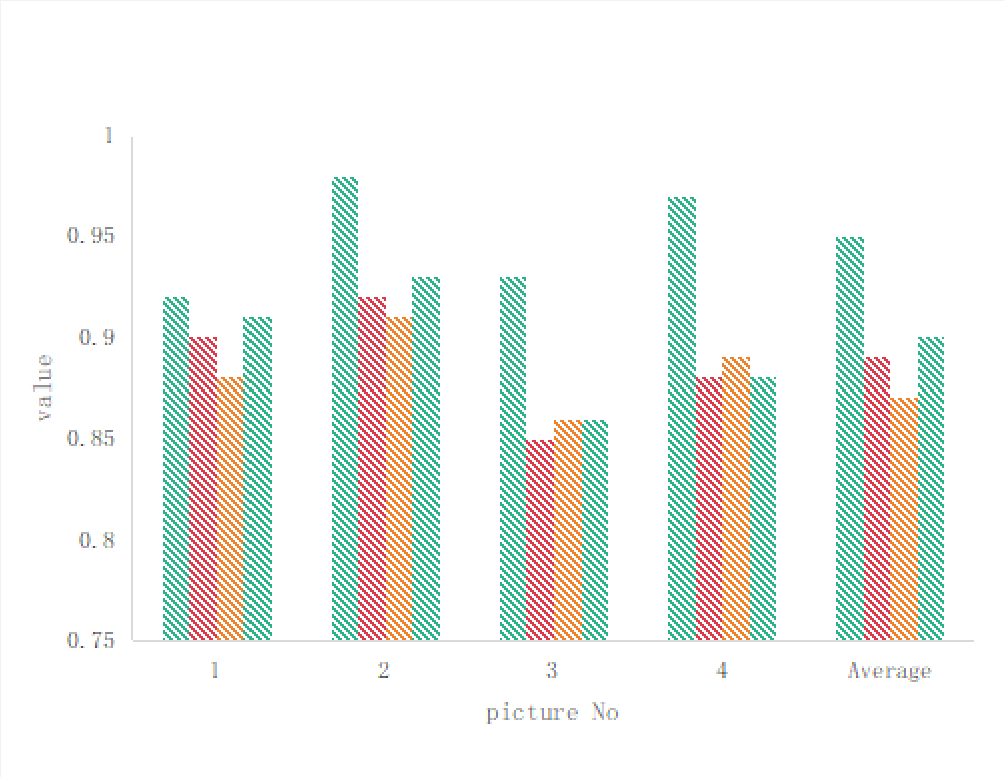

Figure 3. Analysis of segmentation results

The experimental results show that the random forest algorithm segmented the chronological images with an average pixel accuracy of 0.89 and an average region overlap of 0.87.

5. Conclusion

Image segmentation techniques are maturing and are now being used in a variety of industry sectors. In this paper, a random forest algorithm-based image segmentation method is proposed, and the theory involved in the model is elaborated, and finally the actual segmentation effect of the model is tested through experiments. From the experimental results, it can be concluded that the proposed model achieves good results for image segmentation. A comparative analysis of the segmentation effect of the model from different perspectives shows that the model has good generalisation ability. However, there are still some problems to be solved, and there is still room to improve the segmentation effect of the model. The future research direction is to investigate the solutions to the problems of imprecise edge segmentation and overfitting in the model.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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