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Wood species classification based on local edge distributions

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ABSTRACT

The wood species classification system is developed in order to give fair service to the wood industry. An image is characterized mostly by the low level features such as color, shape and texture. Among them texture features play a major role in characterizing the image and the statistical features are found to be efficient for classification. For a better classification result, wood image first has to be preprocessed in order to get meaningful feature extraction. Among various preprocessing techniques, Contrast Limited Adaptive Histogram Equalization is found to be an appropriate method for wood image enhancement. The edges in an image reveal spectral discontinuity, contrast, directional information, and structure pattern. In this paper, in addition to ten statistical features, saliency index is another significant parameter used for texture classification of different wood species. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The computation of saliency index is simple and it is more powerful for recognizing the wood species. The back propagation neural network is used for classification of wood species. 100 number of wood images are used for training the neural network and 50 number of images are used for testing which are taken from prospect data base available for wood images. The percentage of classification accuracy in this work is more encouraging and the classification accuracy is 90%.

1. Introduction

The identification of wood types becomes very important when related to illegal logging, taxes, and the suitability of the product. The experts in identification of wood are very limited in terms of amount, power, and time. And also every type of wood has different strength, durability and density. This makes the industrial price of the wood is different from one another. It is important to differentiate these woods correctly to have them for their appropriate uses. This is because wrongly identified wood could cause huge impact. Because, some woods are being used as important structure of buildings in the construction field.

Wood species classification using computer vision is still a new area of study. Wood species classification requires well-trained experts to study the characteristic seen on the cross-section surfaces of the wood samples obtained under macroscopic view, and when required to, the microscopic view will be studied as well. Today, wood species classification is still mainly conducted by well-trained wood identification experts. It takes a long period of time to train a wood identification expert until he is qualified to identify wood species with a high accuracy. There is a great demand in the industry involving the identification of wood species but the number of wood identification experts is not sufficient to meet the market need.

Computer vision techniques have been used to solve a number of problems that involve the study of patterns, such as text detection, face classification, signature verification, etc. Since each species of wood has a type of pattern observable on the cross-section surfaces, computer vision algorithms can be used to create an automated means to solve the problem.

Computer vision techniques such as texture classification are useful algorithms that can be used to solve problem involving patterns that can be perceived as textures, such as the wood species classification problem where the cross-section surface can be viewed as different textures for different wood species.

The wood species classification system developed by Jordan [1], based on analysis of ultrasonic signals. Many species of wood have subtly different elastic responses due to its own cellular structural characteristics. Thus the recipient waveform that propagates

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through the tangential, radial and longitudinal surfaces of the wood is used to identify the species of the wood according to this technique. The artificial neural network is used to identify the received waveform in terms of species. However, this research involved classification of only four different major species of temperate woods in United States of America, i.e. Oak, Alder, Maple and Pine. The accuracy rate of this system is about 97% using 20 samples for training and 10 samples for testing. Chen and Zhao [2] used microscopic images of wood samples for wood cell recognition. First, a novel 2-D cell image collection system is devised, and the wood cell images are segmented by using a dual threshold segmentation algorithm. Second, a geodesic active contour (GAC) is applied in the segmented binary image to extract the edge contours of multiple cells simultaneously. Third, wood cell recognition is performed based on the Mahalanobis distances calculated by using the principal component analysis (PCA) algorithm.

In the previous research, authors used 20 types of wood, using seven characteristics of RGB image, and the six characteristics of image edge detection [3]. This research provide 85% classification rate. Then Adaptive Neuro Fuzzy Inference System (ANFIS) is used and it is based on the textural features [4]. Five types of wood can be classified using the system. Harjoko et al. [5] developed a classification method using 15 types of wood and it is based on texture analysis of microscopic wood images using Artificial Neural Network Back Propagation Algorithm (ANNBP), and gives the classification accuracy of 95%. It requires magnification of wood images using powerful microscopes. Zhao et al. [6] developed a method that integrates the color, texture and spectral features so as to identify the wood species. Then a fuzzy back propagation neural network is used to perform the classification work, which consists of 4 sub-networks based on the color feature, texture feature and spectral feature. The recognition accuracy is approximately 90% for 5 wood species.

There has not been much development in automatic wood classification system due to the difficulty in obtaining a wide range of wood database, lack of availability of proven techniques for wood classification, current research makes use of expensive devices, availability of human inspectors especially in developing countries. Furthermore, manual examination of the wood sample can be very subjective. These problems motivated us to develop such a system to identify the species of wood without any difficulty.

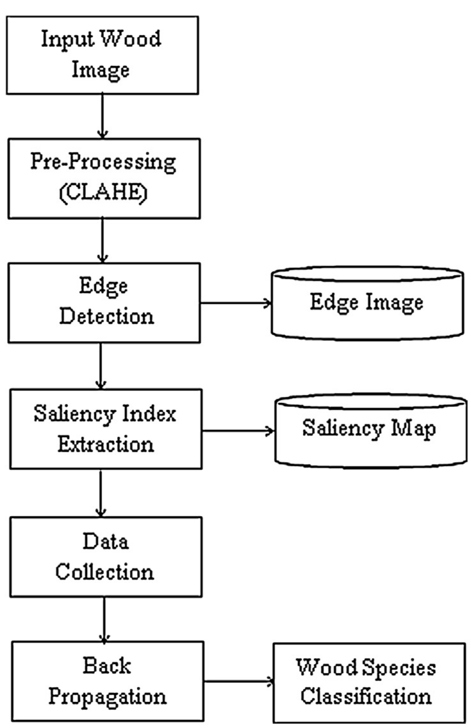

Fig. 1. Workflow for the classification of wood species.

In this paper, saliency index [7] is used for the texture classification of different wood species. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The edge in an image reveals spectral discontinuity, contrast, directional information, and structure pattern. The work presented in this project can be used to classify the wood species based on its texture as shown in Fig. 1.

2. Materials and methods

In this paper wood images are recognized based on the distribution of the edge pixels. Edges are used as the main source of information to compute the saliency in the local window of every pixel. The pre-processing is performed so that the edges in the wood images can be distinguished easily. The pre-processing methods used are histogram equalization, bi-histogram equalization, histogram equalization with Bin Underflow and Bin Overflow (BUBO) method, integral mask filtering approach and Contrast Limited Adaptive Histogram Equalization (CLAHE) method. Among these CLAHE is found to be appropriate for wood images. Then the edges are obtained from the pre-processed image and finally saliency index is obtained from the binary edge image.

2.1. Pre-processing methods

2.1.1. Histogram equalization

Image histogram plots the number of pixels for each intensity value. Histogram manipulation can be used effectively for image enhancement. The intensities can be better distributed on the histogram using histogram equalization. This allows the areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Let 'r' denote the intensities of an image to be processed and 'r' is in the range $[0, L-1]$. Then the transformations (intensity mapping) is of the form $s = T(r)$, where 's' is the output intensity level for every pixel in the input image having intensity 'r'.

2.1.2. Bi-histogram equalization (BHE)

The BHE firstly decomposes an input image into two sub-images based on the mean of the input image. One of the sub-images is the set of samples less than or equal to the mean whereas the other one is the set of samples greater than the mean. Then the BHE equalizes the sub-images independently based on their respective histograms with the constraint that the samples in the formal set are mapped into the range from the minimum gray level to the input mean and the samples in the latter set are mapped into the range from the mean to the maximum gray level. In other words, one of the sub-images is equalized over the range up to the mean and the other sub-image is equalized over the range from the mean based on the respective histograms. Thus, the resulting equalized sub-images are bounded by each other around the input mean, which has an effect of preserving mean brightness.

Let X_m denote the mean of the image X and assume that $X_m \in \{X_0, X_1, \ldots, X_{L-1}\}$. Based on the mean, the input image is decomposed into two sub-images X_L and X_U as given in Eq. (1).

$$X = X_L \cup X_U \quad (1)$$

where

$$X_L = \{X(i,j) | X(i,j) \leq X_m, X(i,j) \in X\} \quad (1a)$$