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Wood Species Classification and Identification System

S. Mohan [1], K. Venkatachalapathy [2], Ashok Kumar Rai [3]
[1]Asst. Professor, [2] Professor,[3] P.G. Student, Dept. of CSE, Annamalai University, Tamilnadu, India
mohancseau@gmail.com

Abstract

Automatic wood recognition has not yet been well established mainly due to lack of research in this area and the difficulty in obtaining the wood database. In this paper, an automatic wood recognition system based on image processing, feature extraction and artificial neural networks was designed. The proto-type PC-based wood recognition system is capable of classifying 30 different tropical Malaysian woods, according to their species based on the macroscopic wood anatomy. Image processing is carried out using our newly developed in-house image processing library referred to as "Visual System Development Platform". The textural wood features are extracted using a co-occurrence matrix approach, known as grey-level co-occurrence matrix. A multi-layered neural network based on the popular back-propagation algorithm is trained to learn the wood samples for the classification purposes. The system can provide wood identification within seconds, eliminating the need for laborious human recognition. The results obtained show a high rate of recognition accuracy, proving that the techniques used are suitable to be implemented for commercial purposes.

Keywords: Grey-level Co-occurrences Matrix, Feature extraction and Artificial Neural Networks.

Introduction

Tropical countries are blessed with an abundance of wood supply. With more demands in timber industries and more tightly controlled international requirements, many of these countries are required to meet tighter security requirements as well as higher technical demands such as more accurate recognition of the correct timber species, prevention of fraud and illegal logging, and Environmental Investigation Agency (EIA) requirements, to name a few. In many timber industries one of the major problems is to find good wood graders. Currently, very few certified officers are involved in the traditional wood identification process. The process of training up experienced officers in performing the job is difficult since the job is no longer considered lucrative and rather laborious. Moreover, the possibility of biasness and mistakes by human wood graders has to be considered. Besides that, it is impractical and cost effective for a human to analyze and identify a large number of timber species.

Tropical rainforests in South-East Asia are blessed with more than 15,000 different plant species, of which about 3,000 species can be categorized as timber species. Major revenues of most countries in South-East Asia are derived from the exportation of wood products. In fact, Malaysia is a top exporter of wood products with the revenue of over USD10 billion in 2006 (Statistical Dept. of Malaysia, 2007). As such, the need for wood recognition is necessary as prices vary greatly among different wood species. Woods are categorized for use in different applications. For example, in order to build a reliable roof truss, only woods with acceptable strength, such as the Neobalanocarpus heimii or the local name change are used and on the other hand, in furniture making, the cheaper Hevea brasiliensis or simply known as rubber woods are used.

Another purpose of identifying wood is to check for fraud as some timber traders tend to mix different types of wood so as to increase their profit margin. Due to pressure from the environmental related Non-government Organizations such as the Environmental International Agency (EIA), many countries have banned the export of endangered species such as the Gonystylus bancanus or locally known as ramin. The identity of the tree in the forest can be easily known by examining their flowers, fruits and leaves. However, once the tree is felled, the identification of the tree becomes very difficult and has to rely on their physical, macroscopic and microscopic features for identification.

In this research, an intelligent recognition system using low cost equipment for the identification of wood species based on the macroscopic features of wood has been designed. This paper has been organized as follows. The next section describes the major factors that have

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motivated this research. In the section that follows, the experimental setup and research methodology which includes how data were collected and prepared and how the major techniques were applied are described. This is followed by a brief description on the development of the automatic wood recognition system from both software and hardware points of view. The results on the performance of the system are next described later and this is followed by the conclusion.

Tropical rainforest has more than 3,000 different types of timber species. According to the Forest Research Institute of Malaysia, out of these about 200 species are being used by the timber industry. Among the major timber consumers are housing developers, wood fabricators and furniture manufacturers where the need for recognition of wood species is necessary. Automatic wood recognition has not yet been well established mainly due to lack of research in this area and the difficulty in obtaining the wood database. In this paper, an automatic wood recognition system based on image processing, feature extraction and artificial neural networks is proposed.

Currently, the examination of the wood sample is done by the experts using naked eye based on the weight, color, odor, feel, texture and surface. The experts must be familiar with features of all types of wood species. A dichotomous key (table for wood texture analysis) is provided as a guideline for the experts to determine the wood species.

Several automatic wood species recognition systems that overcome the errors caused by a traditional wood identification system which based solely on human expertise have been developed. Previous wood species recognition systems are designed based on two approaches: spectrum-based processing system and image-based processing system. In the former category, 21 temperate wood species are classified using fluorescence spectra.

Existing system

Previous wood species recognition systems are designed based on two approaches: spectrum-based processing system and image-based processing system. In the former category, 21 temperate wood species are classified using fluorescence spectra. In the latter category, image processing techniques are used to classify 52 tropical wood species and 112 wood species that belong to hardwoods and softwoods. Yusofet et al. adopted fusion of two feature sets using multi feature extractor technique. Two feature extraction methods were used in this system: co-occurrence matrix approach and Gabor filters. These two extraction methods produced more variation of features and also improved the accuracy rate of the system. Wang et al. proposed a wood surface texture recognition method based on feature level data fusion which uses three types of texture analysis methods.

The three texture analysis methods used are Gray Level Co-occurrence Matrix (GLCM), Gauss-Markov Random Field (GMRF) and wavelet multi-resolution fractal dimension. The fusion method is based on Simulated Annealing Algorithm with memory.In a later development, Khairuddin et al. used feature selection based on genetic algorithm to improve the accuracy of wood species recognition, in particular to reduce the redundant features which are not considered as discriminatory enough for accurate classification.

Proposed system

The proposed system identifies the species of the wood using the textural features present in its barks. Each species of a wood has its own unique patterns in its bark, which enabled the proposed system to identify it accurately. The automatic wood recognition system has not yet been well established mainly due to lack of research in this area and the difficulty in obtaining the wood database. In our work, a wood recognition system has been designed based on pre-processing techniques, feature extraction and by correlating the features of those wood species for their classification.

Texture classification is a problem that has been studied and tested using different methods due to its valuable usage in various pattern recognition problems, such as wood recognition, rock classification. The most popular technique used for the textural classification is Gray-level Co-occurrence Matrices. The features from the enhanced images are thus extracted using the GLCM is correlated, which determines the classification between the various wood species. The result thus obtained shows a high rate of recognition accuracy, proving that the techniques used in suitable to be implemented for commercial purposes.

The proposed technique can be applied for automatic wood recognition. This work is specifically focused on wood recognition and classification using artificial neural network. The design of this technique is based on extensive analytical as well as experimental modeling The wood images are pre-processed using homomorphic filters in order to enhance the image presentation. Homomorphic filtering sharpens features and flattens lighting variations in an image.

Hence, illumination and reflectance on the image can be removed. All images are pre-processed using

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homomorphic filters to enhance image presentation. Homomorphic filtering uses a linear filter to do nonlinear mapping to a different domain and later it was mapped back to the original domain. The algorithm removes all illumination and reflectance on the image of the wood recognition process.

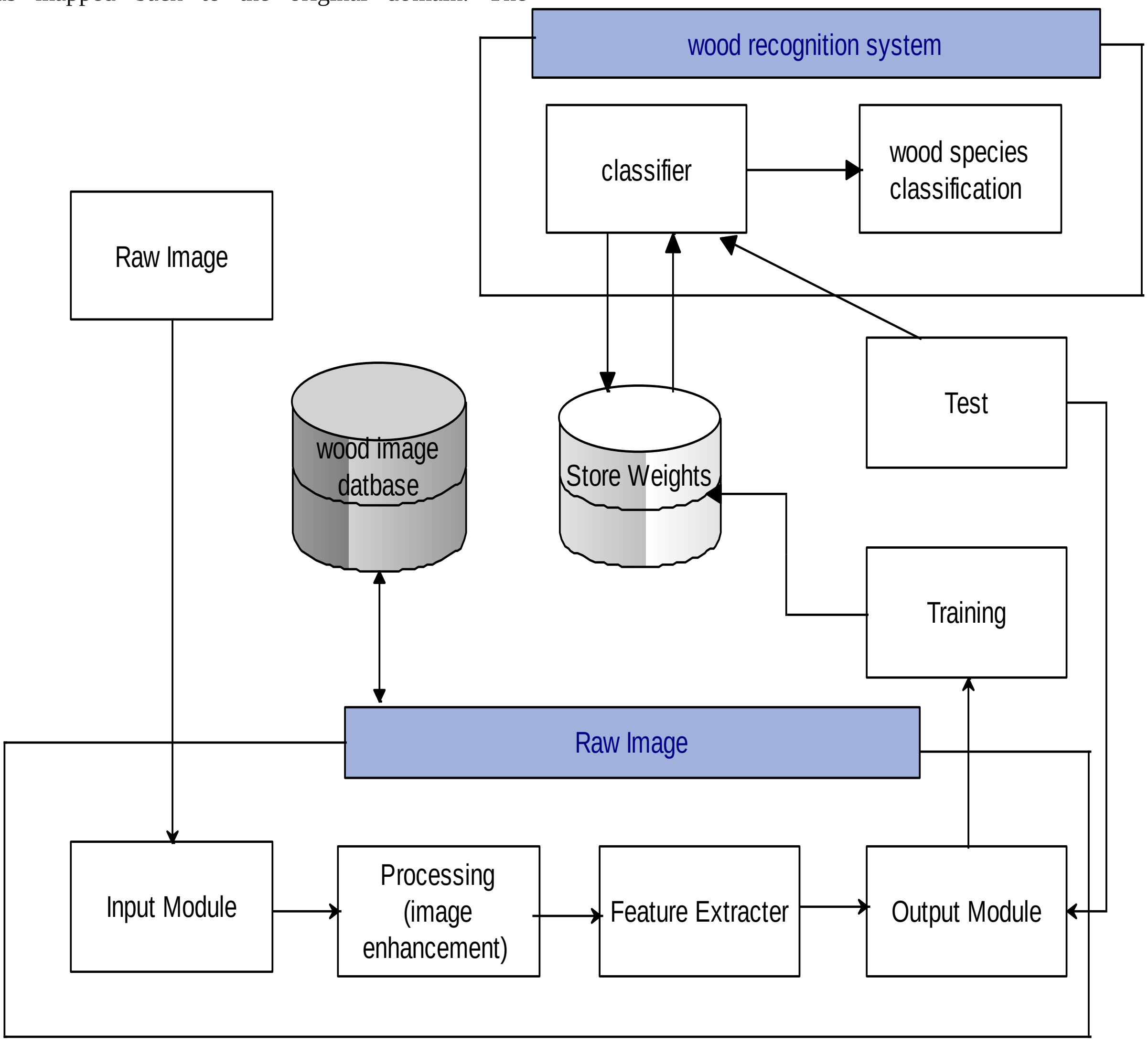

Figure 1: Wood Recognition System.

Block diagram is a diagram of a system, in which the principal parts or functions are represented by blocks connected by lines that show the relationships of the blocks. The block diagram is typically used for a higher level, less detailed description aimed more at understanding the overall concepts and less at understanding the details of implementation. The detailed flow diagram of the proposed system as shown in figure.

Research methodology

Data Collection

The wood samples for this project are obtained from the Forest Research Institute of Malaysia (FRIM). There are 52 wood species in cubic form (approximately 1 inch by 1 inch in size) where 5 cubes are provided for each species. The images of the wood surface are captured by using a specially designed portable camera with 10 times magnification. The size of the each image is 768x576 pixels.

Image Enhancement

After the image is acquired, high-pass spatial filtering is performed to sharpen the image in order to give a clearer definition of the texture properties of the macroscopic wood anatomy. Then the wood images are pre-processed using homomorphic filters in order to enhance the image presentation. Homomorphic filtering sharpens

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features and flattens lighting variations in an image. Hence, illumination and reflectance on the image can be removed. All images are pre-processed using homomorphic filters to enhance image presentation. Homomorphic filtering uses a linear filter to do nonlinear mapping to a different domain and later it was mapped back to the original domain. The algorithm removes all illumination and reflectance on the image.

Image Segmentation

Texture is characterized not only by gray value at a given pixel but also by the gray value 'pattern' in a neighborhood surrounding pixel where the brightness level at a point depends on the brightness levels of neighboring point. A locally adaptive binarization method was used to binarize images. The following output was manifested by the mechanism of pixel value transformation to 1, provided that the value to be larger than the mean intensity (N) value of the present block (16 x 16) to which the pixel adheres and 0, otherwise.

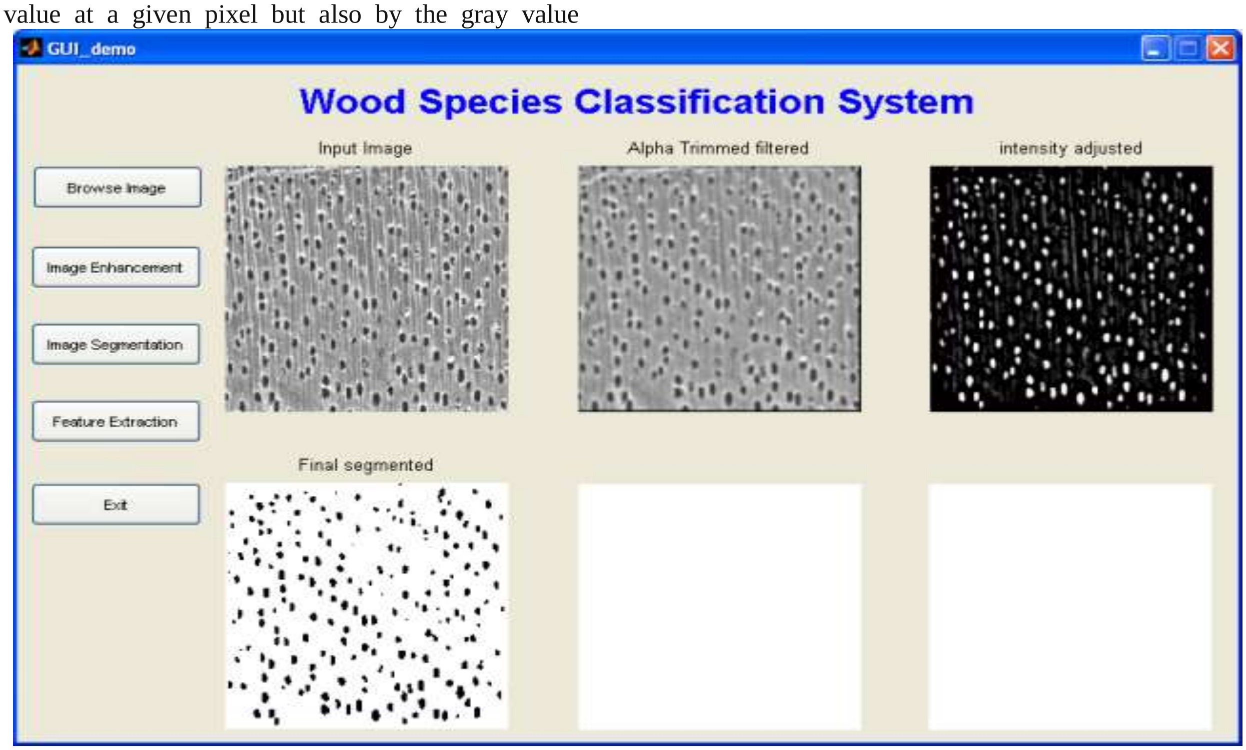

Figure 2: Segmentation of image

Feature Extraction

Due to their stochastic nature, wood textures can be characterized by statistical means into first, second and higher-order statistics. Therefore, a texture analysis method was used to extract the distinct features of each wood. Texture analysis methods have been utilized in a variety of application domains such as remote sensing, surface inspection, medical imaging, and remote sensing. From our investigation of several texture analysis methods, the grey level co-occurrence matrix seems appropriate, though it has never been used in wood recognition application.

In this approach, the textural features of an image *I* is based on the assumption that the texture information is contained in the overall or average spatial relationship which the grey tones in the image *I* have with one another. More specifically, this texture information is adequately specified by a set of grey tone spatial dependence matrices that are computed for various angular relationships and distances between neighboring resolution cell-pairs on the image. The features are derived from these grey tone spatial dependence matrices.

For each wood cube, the co-occurrence matrices are calculated from four directions, which are horizontal, vertical, diagonal 45º and diagonal 135º. A new matrix is formed as the average of these matrices that is used for extracting the features. In this way, the extracted features will be rotation invariant at least for 45° steps of rotation. The final co-occurrence matrix is normalized using Equation to

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transform GLCM matrix into a close approximation of the probability table.

$$P(i,j) = \frac{P_d(i,j)}{\sum_{i,j=0}^{N-1} P_d(i,j)}$$

Where Pd is GLCM matrices value of and N is range of i and j. The total features extracted using the GLCM approaches from each wood sample orientation are given as follows

Angular Second Moment:

$$f_1 = \sum_i \sum_j \{P(i,j)\}^2$$

Contrast:

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{j=1}^{N} P(i,j) \right\}$$

Correlation:

$$f_3 = \frac{\sum_i \sum_j (ij) P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Where μx and μy are mean value and σx and σy are standard deviation

Entropy:

$$f_4 = -\sum_i \sum_j P_{ij} \log(P_{ij})$$

Inverse Difference Moment:

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} P_{ij}$$

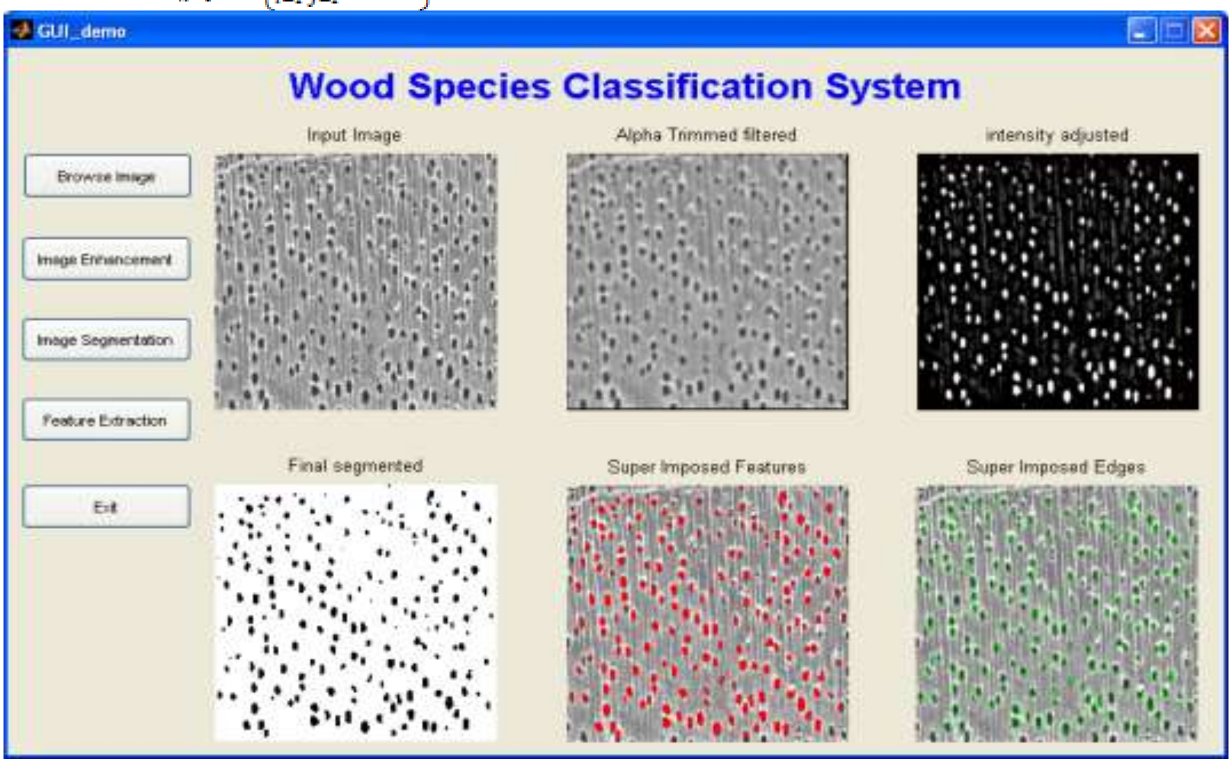

Figure 3: Extracted Features

Classification

The popular Multilayer Perceptron (MLP), Artificial Neural Network (ANN) trained using the Back Propagation(BP) algorithm described in detail in many literatures including (Rumelhartet.al., 1985) is used to classify the wood species. Though other types of ANN can be adopted, since this is a proto-type development and due to time constraint, we opt to use the standard ANN algorithm. Neural Network has been proven to be useful for many types of application. Some of these applications can be found in (Chen,1994), (Hyun,1995), (Irwin et. al,1995), (Omatu et.al.,1995), and (Smith,1993).

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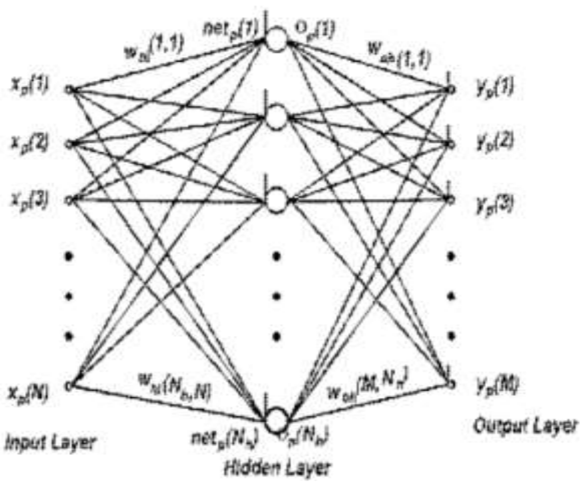

Figure 4: Typical 3 Layer MLP Neural Network

MLP neural networks include units in layers, each layer being composed of nodes and in a fully connected network each node connect subsequent layer nodes. Each MLP has 3 layers minimum including an input layer, one/more hidden layers and output layer. The input layer distributes inputs to other layers. Input nodes have a linear activation without thresholds. Every hidden unit node and output node have thresholds in addition to weights. Hidden unit nodes have nonlinear activation functions and outputs linear activation functions. So, each signal feeding a subsequent layer node has original input multiplied by weight with added threshold and is passed through a linear or nonlinear (hidden units) activation function. Fig.1 reveals a typical 3 layer network. Only 3 layer MLPs are considered in this work as they approximate a continuous function. For actual 3 layers MLP, all inputs are connected to all output directly.

Forward Pass:

The input vector x^0 is transformed into the output vectorx^L, by evaluating the equation

$$x^l(i) = f(u_i{}^l) = f\left(\sum_{j=1}^{n_{l-1}} W^l{}_{ij} x^{l-1} + b^l{}_i\right)$$

for 1 = 1 to L.

Error Computation:

The difference between the desired output d and actual output x^L is computed

$$\delta_i{}^L = f'(u_I{}^L)(d_i - X^L{}_i)$$

Backward Pass:

The error signal at the output units is propagated backwards through the entire network, by evaluating

$$\delta_i{}^{L-1} = f'(u_I{}^{L-1}) \sum_{i=1}^{n_j} \delta_i{}^l w_{ij}{}^l$$

from l = L to 1.

Learning Updates:

The synaptic weights and biases are updated using the results of the forward / backward passes

$$\Delta w_{ij}{}^l = \eta \delta_i{}^l x_j{}^{l-1}$$

$$\Delta b_i{}^l = \eta \delta_i{}^l$$

These are evaluated for l = 1 to L. The order of evaluation doesn't matter.

Results and discussions

Several MLP models were experimented using 20 input features extracted from the GLCM approach and an example of the input features of several wood samples is shown as in Table 1.In this prototype, twenty different types of tropical woods have been randomly acquired from the FRIM wood library. A total of 1,753 images were used for the ANN training while another 196 images were used for testing. Experiments were conducted to determine a suitable MLP model for use in the recognition application. The accuracy rate of the system is determined by applying all the test images in the Database Module. As the accuracy of the MLP models are dependent on a number of factors such as the number of hidden neurons, choice of the learning and momentum parameters, the initial weights, and the number of input features, in these experiments we chose these parameters judiciously such that the performance of the system achieved an accuracy of slightly more than 95% . At this stage we found that it was difficult to improve the accuracy further and thus we stopped the experiments upon achieving such accuracy rate.

Conclusion

In this project, an automatic visual inspection system for the recognition of tropical wood species based on artificial intelligence techniques has been proposed. The system was objectively designed to be cost-effective and as a means to replace wood inspectors due to difficulty in recruiting them as the job is rather laborious. The system has been developed based on an in-house developed image processing library referred to as VSDP. Using the VSDP module vs. CAM, CCD cameras of various types can be interfaced to the PC to acquire the wood image. A variety of image

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processing techniques can be applied using the VSDP modules to enhance the image. In this design we applied the GLCM approach to extract the features from the macroscopic wood anatomy.

This GLCM algorithm is robust to rotation such that the wood cubes can be placed under the camera in any orientation. An ANN model based on the popular BP-trained MLP has been incorporated into the software which can be used to train the wood data acquired in the Database Module. The system shows a high rate of accuracy of more than 95% recognition success of 20 different tropical wood species. A more enhanced version of the system is now currently being improved for higher accuracy based on a variety of feature extraction techniques such as wavelet packet analysis and the Gabor filter approaches.

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