DESIGN OF AN INTELLIGENT WOOD SPECIES RECOGNITION SYSTEM

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Abstract : 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 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 is suitable to be implemented for commercial purposes.

Keywords: Image processing, Texture analysis, Wood recognition, Grey-level co-occurrences matrix, Neural networks.

1. INTRODUCTION

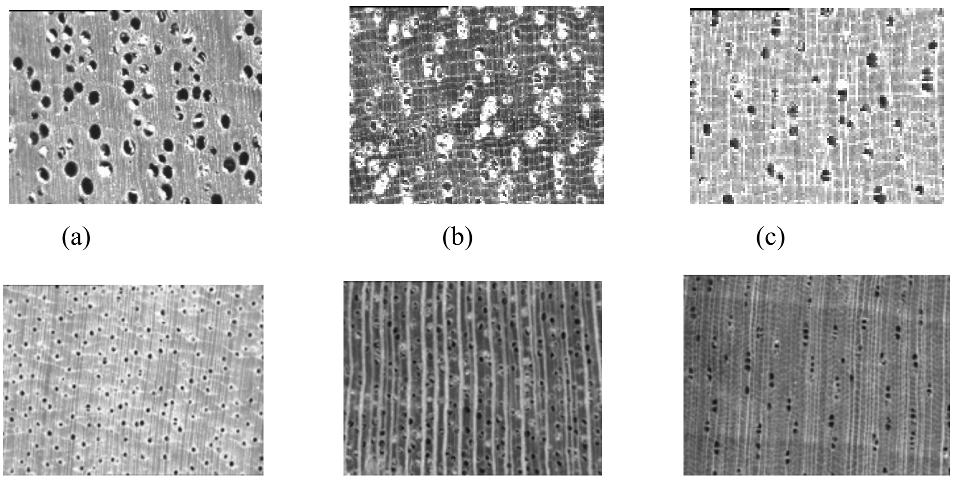
Tropical rainforests in South-East Asia are blessed with more than 15,000 different plant species of which about 3,000 species can be categorised as timber species. Major revenues of most countries in South-East Asia are derived from the exportation of wood products. In fact, Malaysia is a top exporter 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 *chengal* 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 on 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 Organisations such as the Environmetal 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 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.

2. MOTIVATION FOR RESEARCH

It takes a long time to train a person to be competent in wood identification. Furthermore, manual examination of the wood sample can be very subjective. At present, timber is examined by using the naked eye or sometimes with the aid of a magnifier (Menon, 1993). In addition to the macroscopic features of wood, physical features such as weight (different moisture content), colour (variation), feel, odour, hardness, texture, and surface appearance are also considered. For unknown specimen, usually dichotomous keys are used where a step by step analytical procedure on the examination of the wood structure is provided. Figure 1 shows an example of the macroscopic features of six different wood species in Malaysia. These images were captured using a Picolo CCD camera with 10x magnification. It can be observed that at 10 times magnification, these woods can be distinguished, though not so easily and quickly, due to the difference in the structure. Thus, there is an urgent need to use a better way of wood identification like automatic visual inspection systems incorporating techniques such as image processing, statistical feature extraction and artificial neural networks.

Vision technology has existed in the forest product industry since the early 1980s. Most research has been in the development of automatic visual inspection systems in the wood industry for the purpose of grading, trimming and edging based on the quality of the wood and the presence of defects. These machines used technologies and devices such as ultrasound, microwave, nuclear magnetic resonance, X-ray, laser ranging, cameras and spectrometers which are rather expensive (Conners *et al.*, 1997). In a related work previously, they designed a computer vision system for locating and identifying defects on lumber and automatically grade the boards based on the output of the vision system (Conners *et al*, 1989). Another wood defect classification system is based on self-organizing feature construction and neural network classification by (Lampinen and Smolander, 1996). (Kauppinen, 1999) developed a colour based visual inspection method for wood properties such as sound knots and dry knots which are useful for wood grading.



(a) (b) (c)

(d) (e) (f)

Fig. 1. Six examples of macroscopic anatomy images of Malaysian wood: (a) bintangor, (b) nyatoh , (c) sesendok, (d) ramin, (e) mersawa and (f) jelutong.

(Jordan, 1998) developed a wood species classification system based on the analysis of ultrasonic signals. Many species of wood have subtly different elastic responses due to its own cellular structural characteristics. Thus, the recipient waveform which propagates through the tangential, radial and longitudinal surface of the wood is used to identify the species of wood according to this technique. Then artificial neural network is used to classify the received waveforms in terms of the species. However, this research involves classification of only four different major species of temperate woods in the United States of America that is oak, alder, maple and pine. The accuracy rate for this system is about 97% using 20 samples for training and 10 samples for testing.

Another closely related research in wood species identification is by (Brandtberg, 2002) which classify individual tree crowns into respective species groups, using high spatial resolution infrared colour aerial photographs. In this type of digital image, the trees are visible as individual objects. The number of acquired set of photographs to classify using this method are rather large using the applied grade of membership (GoM) model, which is suitable for dealing with large datasets.

The extent of each tree crown in the image is defined using a previously published procedure. Based on colour information (hue), an optimal fuzzy thresh-holding technique divides the tree crown universal set into a dominant set and also into its minor complement. Nine different features of each image object are then estimated, and transformed using principal component analysis (PCA). The GoM model needs initial membership values, which are estimated using an unsupervised fuzzy clustering approach of small sub-areas (branches in the tree crowns) and their corresponding digital numbers in each colour band (RGB-images). Classification is obtained based on three outputs: (1) coniferous/deciduous, (2) scotspine/norway spruce, and (3) birch/aspen. The accuracies (ground patches excluded), using the supervised GoM model with cross validation, are 87%, 76%, and 79%, respectively for each type of species. The accuracy for the compounded system is 67% which is rather low. These two works made use of expensive devices in trying to recognize rather few types of species. Other than these two notable works, there has not been much development in automatic wood recognition, perhaps due to the following factors: (1) difficulty in obtaining a wide range of wood database, (2) lack of availability of proven techniques for wood recognition, (3) current research makes use of expensive devices and (4) availability of human inspectors especially in developing countries.

In this research we are involved in designing an automatic wood recognition system that can classify the species of tropical timber. Our intention was to use a PC and inexpensive supporting devices such as a CCD camera and an in-house developed lighting unit using light-emitting diode (LED) arrays. Image processing techniques are used for enhancing the image using our in-house developed image processing library which we named Visual System Development Platform (VSDP). Our research is also involved in finding suitable algorithms for extracting the correct features from the wood cubes prepared by the Forest Research Institute of Malaysia (FRIM). Features extracted should be rotation-invariant as it would be cumbersome to always place the wood in a certain orientation during the data acquisition. Through our investigation we found that the grey-level co-occurrence matrix approach or GLCM is suitable for such purpose. Classification is then based on the popular back-propagation algorithm (BP) based on 20 features extracted from each wood species.

3. RESEARCH METHODOLOGY

The research methodology can be described from the following points; data collection, data acquisition, image enhancement, feature extraction and classification using neural networks. A block diagram of the procedures in the wood recognition system is shown as in Fig. 2.

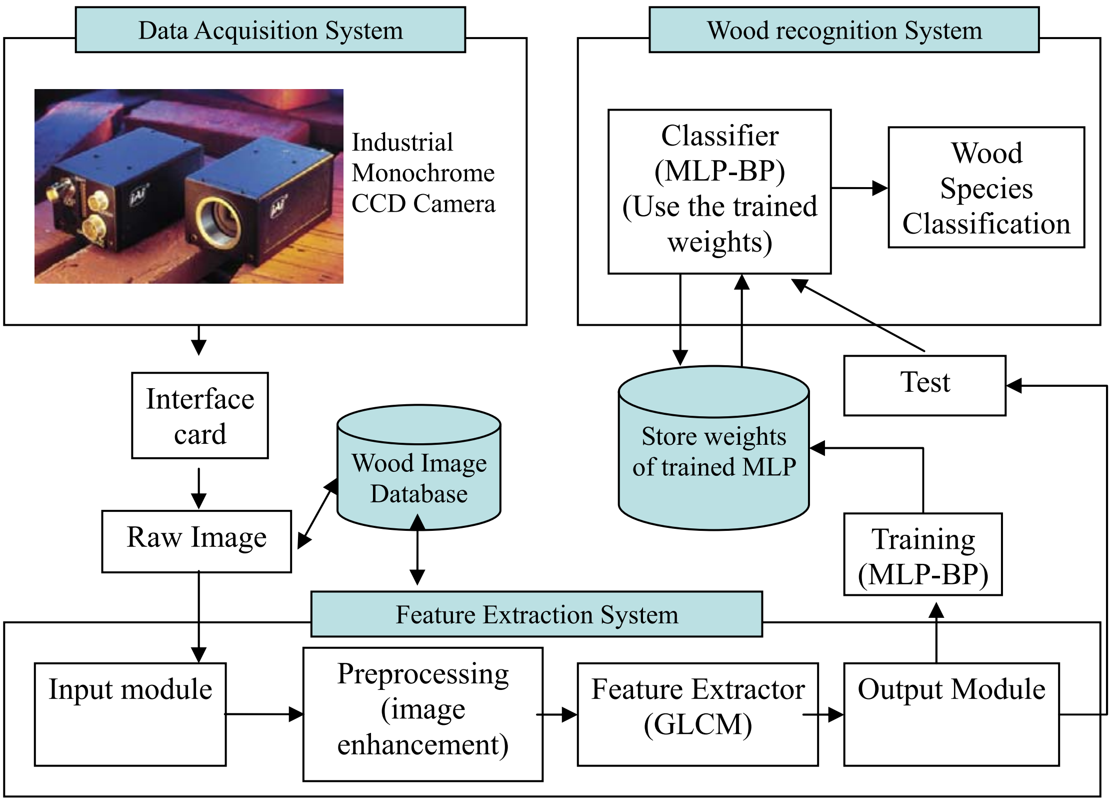


Fig. 2. A block diagram showing the procedures of the wood recognition system.

3.1 Data Collection

Authenticated wood samples were obtained from the FRIM wood collection library and cut into 2-centimetre cubes. These samples were boiled until they were soft enough to be cut cross-sectionally. Each wood has been carefully labeled to avoid wrong identification. The sectioning was carried out by the use of a sliding microtome The macroscopic anatomy of the wood cube is extracted in our experiments using low cost CCD cameras instead of the microscopic thin-layer wood anatomy identification which need more expensive equipment. Research is currently being carried out to develop a faster method of preparing the wood cubes using special tools by our industrial counterpart.

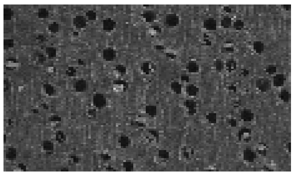
3.2 Image Data Acquisition

The experimental system has been set up to acquire the images of the wood macroscopic anatomy using the industrial monochrome CCD camera (JAI CV-M50 type) with a 40mm extension tube lens as shown in Figure 3. It is interfaced through a EureCard PICOLO interface card which is compatible with Windows 95 / 98 / 2000 / NT and DOS-32 bit and supports real-time transfer of full resolution images up to 768 x 576 pixels. The wood recognition system software is implemented in Visual C++ 6.0 using the in-house developed VSDP image library. This library provides a variety of image processing procedures to acquire good images of the wood for identification including the camera acquisition function for a variety of camera interfaces. The images of the wood samples are acquired using the functions from the *vsCam* module of VSDP which is a module for camera controlled and data acquisition. The lighting is to remain constant throughout the data acquisition of training and testing data. A clamp is used to hold the wood under the lens to be maintained constantly over a specified distance and also to avoid image blurring. A database module of the wood images acquired has been developed in the software using Microsoft Access 2003 and Sequence Query Language (SQL).

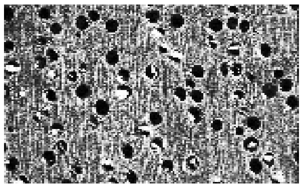
Fig 3. A CCD camera with a 40mm extension tube is used to acquire the macroscopic wood anatomy.

3.3 Image Enhancement

A variety of image processing techniques are available using VSDP. After the image is acquired, high-pass spatial filtering (Gonzalez and Woods, 1992) is performed to sharpen the image in order to give a clearer definition of the texture properties of the macroscopic wood anatomy. This function was implemented using the high-pass filtering function available in the VSDP library. Next, contrast enhancement was done to the iris images which was then followed by Histogram equalization to enhance the wood images. An example of image enhancement using the two procedures of the VSDP Image Library is shown in Fig. 4.



(a)



(b)

Fig. 4. Two procedures which are used to enhance the image quality using VSDP Image Processing Library: (a) Image Sharpening using high-pass filter and (b) Contrast enhancement using histogram equalization

3.4 GLCM Feature Extractor

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 (Jain et al., 2000). From our investigation of several texture analysis methods, the grey level co-occurrence matrix (GLCM) seems appropriate (Haralick 1973, 1979), 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.

The GLCM approach can be described as follows. Consider $\{I(x,y), 0 \le x \le N-1, 0 \le y \le N-1\}$ such that it denotes an $N \times N$ image with G grey levels. The $G \times G$ grey level co-occurrence matrix $P_\mathbf{d}$ for a displacement vector **d** = *(dx, dy)* is defined as follows. The entry *(i,j)* of $P_\mathbf{d}$ is the number of occurrences of the pair of grey levels *i* and *j* which are a distance **d** apart. Formally, it is given as in Equation (1) where: $(r,s),(t,v) \in N \times N, (t,v) = (r+dx, s+dy)$, and $|\cdot|$ is the cardinality of a set.

$$P_d(i,j) = \left|\{((r,s),(t,v)) : I(r,s) = i, I(t,v) = j\}\right| \quad (1)$$

For each wood cube, the co-occurrence matrices are calculated from four directions, which are horizontal, vertical, diagonal 45^o and diagonal 135^o. 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 (2) to transform GLCM matrix into a close approximation of the probability table.

$$P(i,j) = \frac{P_d(i,j)}{\sum_{i,j=0}^{N-1} P_d(i,j)} \quad (2)$$

Where P_d is GLCM matrices value of and N is range of i and j.

The total features extracted using the GLCM approach from each wood sample orientation are given as follows:

1. Angular Second Moment

$$f_1 = \sum_i \sum_j \{P(i,j)\}^2 \quad (3)$$

2. Contrast

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{j=1}^{N} P(i,j) \right\} \quad (4)$$

3. Correlation

$$f_3 = \frac{\sum_i \sum_j (ij) P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (5)$$

Where μ_x and μ_y are mean value and σ_x and σ_y are standard deviation.

4. Entropy

$$f_4 = -\sum_i \sum_j P_{ij} \log(P_{ij}) \quad (6)$$

5. Inverse Difference Moment

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} P_{ij} \quad (7)$$

3.5 Wood Species Classification Using Artificial Neural Networks

The popular multilayer perceptron (MLP) artificial neural network (ANN) trained using the backpropagation (BP) algorithm described in detail in many literatures including (Rumelhart et.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 have 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). 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 and the list is given as in Table 2. 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.

Table 1 Twenty feature values are obtained from the GLCM approach for training the MLP. The last column states the type of wood.

Pattern	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	TARGET	Wood
1	0.242	0.314	0.179	0.212	0.103	0.095	0.361	0.274	0.744	0.744	0.741	0.741	0.722	1.000	0.476	0.574	0.297	0.149	0.475	0.402	00000001	Bintangor
2	0.196	0.257	0.126	0.184	0.269	0.283	0.783	0.500	0.804	0.804	0.798	0.801	0.394	0.567	0.166	0.342	0.542	0.446	0.764	0.611	00000001	Bintangor
3	0.117	0.173	0.077	0.099	0.262	0.223	0.660	0.516	0.622	0.622	0.617	0.618	0.428	0.713	0.245	0.325	0.525	0.371	0.697	0.626	00000001	Bintangor
4	0.070	0.082	0.034	0.038	0.161	0.206	0.482	0.459	0.280	0.279	0.276	0.276	0.395	0.478	0.156	0.187	0.426	0.381	0.624	0.604	00000010	Durian
5	0.058	0.069	0.025	0.028	0.148	0.166	0.433	0.423	0.276	0.275	0.272	0.272	0.376	0.468	0.140	0.159	0.449	0.391	0.641	0.625	00000010	Durian
6	0.045	0.056	0.015	0.020	0.189	0.221	0.538	0.494	0.489	0.488	0.485	0.485	0.293	0.379	0.077	0.113	0.514	0.472	0.715	0.684	00000010	Durian
7	0.043	0.062	0.016	0.022	0.323	0.319	0.775	0.694	0.411	0.411	0.406	0.406	0.217	0.349	0.029	0.068	0.679	0.616	0.881	0.842	00000100	Melunak
8	0.043	0.062	0.016	0.022	0.323	0.319	0.775	0.694	0.411	0.411	0.406	0.406	0.217	0.349	0.029	0.068	0.679	0.616	0.881	0.842	00000100	Melunak
9	0.039	0.053	0.010	0.016	0.376	0.429	0.964	0.817	0.500	0.499	0.493	0.495	0.216	0.266	0.006	0.045	0.776	0.765	1.000	0.955	00000100	Melunak
10	0.620	0.712	0.502	0.529	0.236	0.368	0.679	0.695	0.297	0.296	0.292	0.291	0.542	0.632	0.318	0.338	0.440	0.437	0.651	0.641	00001000	Nyatoh
11	0.468	0.560	0.370	0.401	0.270	0.354	0.735	0.701	0.273	0.272	0.268	0.267	0.495	0.627	0.271	0.317	0.481	0.452	0.688	0.664	00001000	Nyatoh
12	0.617	0.732	0.505	0.541	0.256	0.327	0.695	0.667	0.254	0.253	0.249	0.249	0.547	0.686	0.321	0.353	0.444	0.412	0.646	0.629	00001000	Nyatoh
13	0.091	0.149	0.057	0.073	0.176	0.170	0.515	0.392	0.603	0.603	0.599	0.600	0.306	0.631	0.132	0.219	0.362	0.222	0.545	0.468	00010000	Perupok
14	0.100	0.160	0.066	0.077	0.171	0.163	0.496	0.393	0.576	0.576	0.572	0.573	0.329	0.655	0.169	0.212	0.365	0.224	0.537	0.487	00010000	Perupok
15	0.096	0.158	0.065	0.074	0.176	0.158	0.492	0.393	0.583	0.583	0.579	0.579	0.307	0.636	0.148	0.196	0.354	0.203	0.521	0.470	00010000	Perupok
16	0.072	0.111	0.044	0.047	0.072	0.066	0.286	0.246	0.134	0.134	0.132	0.132	0.406	0.618	0.210	0.239	0.361	0.249	0.540	0.509	00100000	Ramin
17	0.059	0.091	0.032	0.036	0.072	0.085	0.301	0.262	0.213	0.212	0.210	0.210	0.402	0.595	0.199	0.231	0.412	0.322	0.602	0.569	00100000	Ramin
18	0.094	0.149	0.064	0.066	0.038	0.027	0.212	0.179	0.062	0.061	0.059	0.059	0.490	0.771	0.292	0.312	0.276	0.141	0.448	0.417	00100000	Ramin
19	0.043	0.068	0.017	0.021	0.266	0.301	0.682	0.637	0.441	0.440	0.436	0.436	0.312	0.454	0.124	0.144	0.636	0.564	0.825	0.800	01000000	Sepetir
20	0.050	0.075	0.022	0.028	0.269	0.301	0.714	0.618	0.504	0.503	0.499	0.499	0.327	0.447	0.129	0.160	0.626	0.564	0.823	0.785	01000000	Sepetir
21	0.062	0.093	0.031	0.038	0.278	0.293	0.719	0.621	0.587	0.586	0.581	0.582	0.304	0.413	0.111	0.136	0.655	0.593	0.850	0.815	01000000	Sepetir
22	0.054	0.091	0.027	0.034	0.190	0.166	0.483	0.447	0.859	0.859	0.856	0.855	0.270	0.498	0.090	0.140	0.503	0.364	0.671	0.630	10000000	Sesendok
23	0.090	0.131	0.052	0.068	0.173	0.177	0.486	0.423	0.886	0.886	0.882	0.882	0.319	0.540	0.117	0.208	0.468	0.346	0.657	0.587	10000000	Sesendok
24	0.084	0.121	0.049	0.057	0.191	0.192	0.475	0.483	0.874	0.874	0.870	0.870	0.324	0.521	0.128	0.164	0.504	0.390	0.678	0.651	10000000	Sesendok

Table 2 Number of images used for training and testing of each wood species

Species Name	Local Trade Name	Train Images	Test Images
Calophyllum curtisii	Bintangor	81	10
Durio lowianus	Durian	90	10
Pentace triptera	Melunak	90	10
Palaquium impressinervium	Nyatoh	90	10
Lophopetalum javanicum	Perupok	81	9
Gonystylus bancanus	Ramin	99	11
Sindora coriacea	Sepetir	80	9
Endospermum diadenum	Sesendok	90	10
Parashorea densiflora	Gerutu	89	10
Koompassia malaccensis	Kempas	63	7
Albizia splendens	Kungkur	81	9
Anisoptera costata	Mersawa	90	10
Neobalanocarpus heimii	Chengal	90	10
Dyera costulata	Jelutong	90	10
Intsia palembanica	Merbau	90	10
Artocarpus kemando	Keledang	90	10
Kokoona littoralis	Mata ulat	99	11
Campnosperma auriculatum	Terentang	90	10
Myristica iners	Penarahan	90	10
Tetramerista glabra	Punah	90	10

4. SOFTWARE DEVELOPMENT AND EXPERIMENTS

The software for the wood recognition system is developed using the Visual C++ programming language and the main subroutine blocks are shown as in Fig. 2. The Main Module has a graphical user interface (GUI) and controls the other subroutines of the software. The user can acquire the wood image data correctly by tuning the CCD camera parameters through the Camera Control/Data Acquisition Module which uses VSDP Image Library routines. Several types of cameras are allowed to be connected at the same time to the PC but the user can choose only one camera at a time. Before each wood cube is placed under the camera it is carefully labeled and once the image of the wood cube is extracted, the user can input informative data into the Database Module such as the date of the sample collected, name of person who discovered the wood, and the place where it was found. A screenshot of the Database Module showing this information is as shown in Fig. 6.

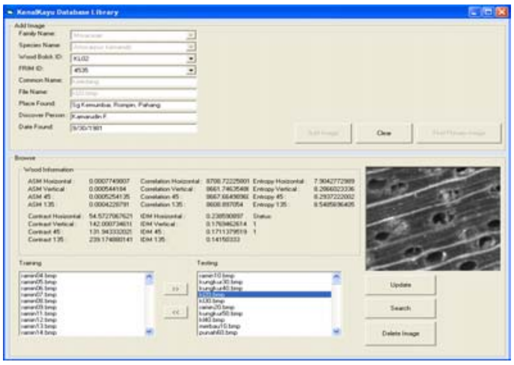


Fig. 6. The Database Module of the wood recognition system containing information such as wood image, FRIM identification code, local name, scientific name, place and date found and founder. The middle part shows the features extracted using the GLCM approach.

Image enhancement routines are available in the Image Processing Module which has been developed using the VSDP Image Library. By invoking this module, the image of the wood acquired is enhanced through a set of procedures namely, smoothening, sharpening, binarizing and contrasting and an example of the results of some of these procedures are shown as in Fig. 7. The features of the enhanced image are then extracted using the Feature Extraction Module consisting of the GLCM approach. A set of 5 features are extracted from each orientation and thus providing a total of 20 input features to the ANN for each wood image. By invoking the ANN Module, a MLP model can be configured to have one or two hidden layers with a maximum of 150 hidden neurons in each layer. Other parameters of the MLP can also be set in prior before it is trained using the BP algorithm. The MLP has to be trained for the entire wood species in the database and using the Database Module the training set can be chosen. The performance of the trained MLP can be tested using the Recognition Module. Usually this is done offline where a set of test images can be chosen from the Database Module.

5. APPLICATION OF WOOD RECOGNITION SYSTEM

Once the MLP has been trained the weights are automatically saved. When the software is re-started to be used, the saved weights after the last training stage will be automatically re-called for use in the recognition stage. The user can set the Wood Recognition Software for online mode in the Main Module. If the user wishes to change or adjust the camera settings, this can be done through the Camera Control/Data Acquisition Module. Once the image is correctly acquired such as when contrasted and focused which the user can observe in the monitor, the Recognition Module can be invoked to get the results of the recognition which is shown as in Fig. 8. The current macroscopic wood anatomy of the actual wood under observation is presented each time and the Recognition Module also show the macroscopic wood anatomy of the answer it gives each time. This makes the system rather attractive to be used as the user can compare the current wood anatomy under observation and that of the answer given by the system. Each time our system is also able to provide two other alternative answers which are the second and third best scores of the ANN output as shown in Fig. 9 when invoked making it rather attractive if the first answer is not highly reliable. Another observation is that the recognition speed of the wood recognition system is highly fast. Using a Pentium IV 2 GHz PC, the wood species is recognized in about 1 second making it faster than a human inspector.

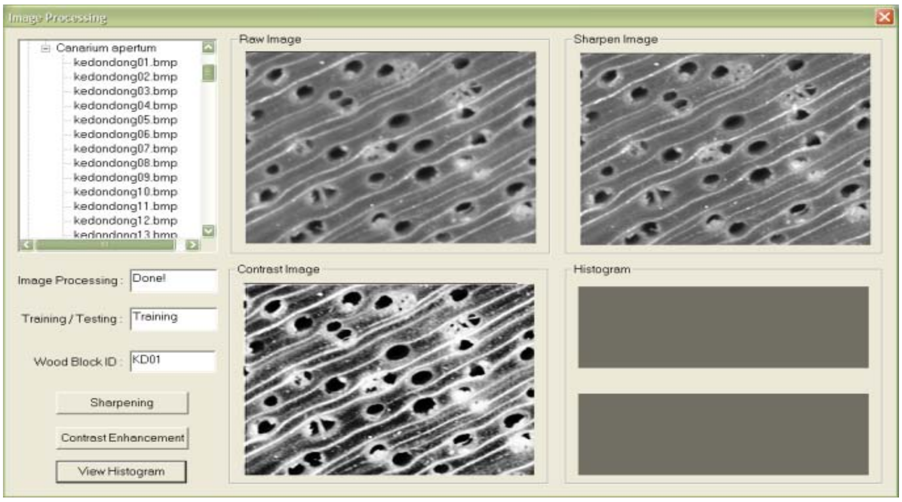


Fig. 7. Example of a screenshot of the wood image enhanced using the Image Processing Module.

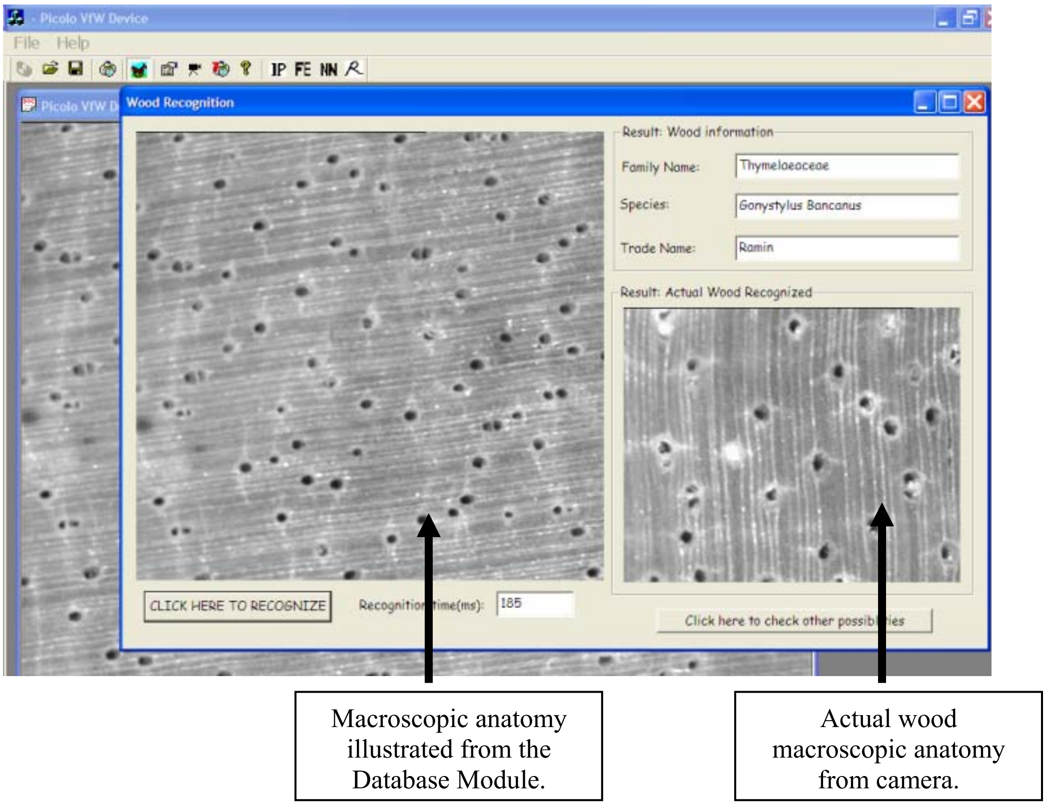


Fig. 8. Example of the results given by the Recognition Module of the Wood Recognition System.

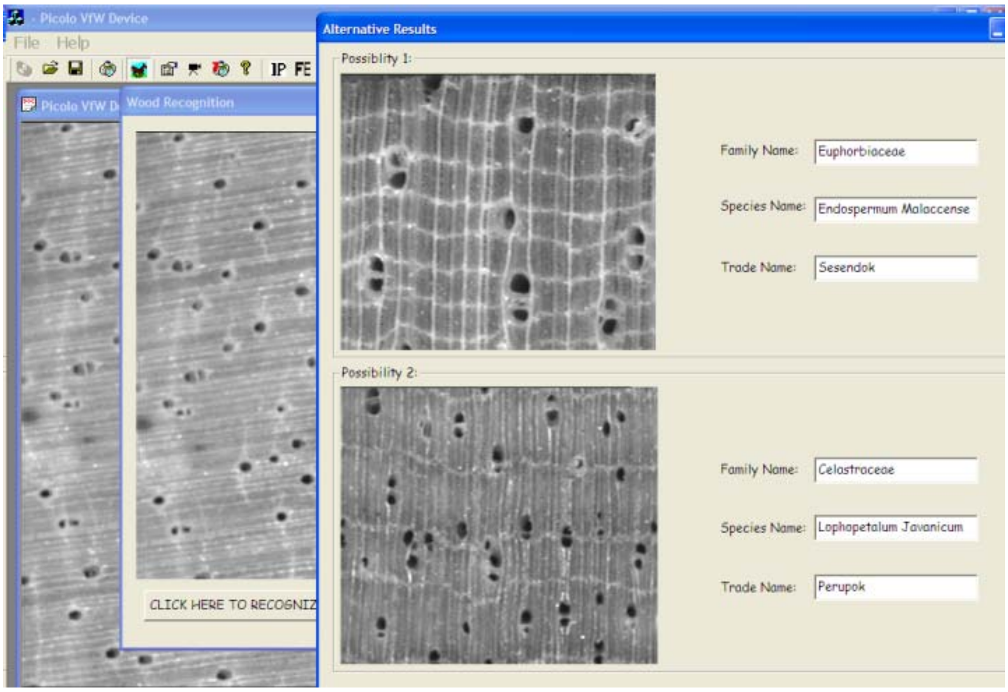


Fig. 9. Example showing two other alternative answers together with illustrations of their respective macroscopic anatomies given by the Recognition Module of the Wood Recognition System.

6.0 CONCLUSION

In this paper, 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 vsCAM, CCD cameras of various types can be interfaced to the PC to acquire the wood image. A variety of image 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. Several pattern classifiers are being investigated such support vector machine (SVM) and other ANN paradigms to further improve the classification of the wood species. A portable type of wood recognition device is also currently being designed. It is hoped that the research can further enhance the application of artificial intelligence based products in other application areas in the timber industry.

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