World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:3, No:4, 2009

Wood Species Recognition System

Bremananth R, *Life Member, IETE,* Nithya B, and Saipriya R

Abstract—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. 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 (GLCM). 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.

Keywords—Correlation, Grey Level Co-Occurrence Matrix, Probability Density Function, Wood Recognition.

I. Introduction

IDENTITY of a tree 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 patterns present in their barks for identification. In our work a wood recognition system using low cost equipment for the identification of wood species based on the pattern of the wood has been designed. It takes a long time to train a person to be competent in wood identification. Further more, 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.

An intelligent wood recognition system was developed by Marzuki Khalid [1], to identify the wood species based on the macro images of the wood samples. In this paper, an automatic visual inspection system for the recognition for the tropical wood species based on artificial intelligence techniques has been proposed. The system has been developed based on an in-house developed image-processing library referred to as Visual Studio Development Platform (VSDP). Using the VSDP module, vsCAM, Charge Coupled Device (CCD) cameras of various types are interfaced to acquire the wood image. GLCM method has been used to extract features from the macroscopic wood anatomy and Artificial Neural Network model based on the popular Back Propagation-trained Multilayer Perceptron has been incorporated into the software that can be used to train the wood data acquired in the database module.

A wood species classification system developed by Jordan [2], 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 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 4 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.

A wood defect classification system was developed based on self-organizing feature construction and neural network classification by Lampinen and Smolander [3]. Kauppinen [4] developed a color based visual inspection method for wood properties such as sound knots and dry knots that are useful for wood grading. Another closely related research in wood species identification is by Brandtberg [5], that classify individual tree crowns into respective species groups, using high spatial resolution infrared color 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 data etc. The extent of each tree crown in the image is defined using a previously published procedure. Based on color 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 color band (RGB-images). Classification is obtained based on three outputs: (1) coniferous/deciduous, (2) Scot spine / 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% that 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

R.Bremananth is Professor with Dept. of Computer Applications, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India-641008 (91-422-2461588,2460088, e-mail: bremresearch@gmail.com , see http://www.srec.ac.in).

R.Saipriya & B.Nithya are research students with Dept. of Computer Technology, Sri Ramakrishna Engineering College, Coimbatore, Tamil Nadu, India. (e-mail: sai _ramu@ymail.com).

Manuscript received Augest 14, 2009; revised Augest 31, 2009.

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.

Gabor filter based texture classification was discussed by Jing Yi Tou [6]. A comparison between the efficiency of features extraction using Gabor Filters and Gray-Level Co-Occurrence Matrices was performed. It was found that the efficiency of GLCM was better than Gabor Filters. Then the texture classification seemed to have a high rate of accuracy when it was performed with both the methods of GLCM and Gabor Filters. The preliminary steps involved in our work involve the collection of wood images through a digital camera of better resolution, which is explained in the section III A. The acquired wood images are resized and pre processing techniques are pursued for the image enhancement, explained in the section III B. Then necessary features are extracted from the enhanced wood images, which are explained in the section III C. Features extracted should be rotation invariant, as it would be burdensome to always place the wood in a certain orientation during the data acquisition.

II. Overview of the Proposed System

At the outset of the process, the input images for both testing and training are acquired using a high resolution digital camera. Before the wood images are tested for its relevant species, it is mandatory for the system to be trained with all possible species available. So that, a wood image that are to be recognized is matched or correlated with already trained species to find its possible outcome. The training of the wood species includes two steps pre-processing techniques and feature extraction. The pre-processing further has two processes, resizing and converting the images to gray. As the images are loaded into the system they are resized to the size 256 X 256 by altering its width and height and converting them to gray using the standard gray conversion formula. These resized gray images are stored on flat files which are used later for the further processing. After the pre-processing the features from each wood image are extracted. Gray Level Co-occurrence Matrix Algorithm is used to retrieve the features. The classification of the wood species is done with the features extracted for each image.The complete description and overview of the system is illustrated in Figure 1.

For each wood image 20 different features are extracted and stored in a separate flat file. The extracted features of a wood image are compared with the features extracted from the test image during testing process which is described as follows. The testing processing contains the same step as the training. The images are set into the pre processing steps and the features are extracted using GLCM. Correlation between the test image and the training images occurs in addition during testing process. The feature of test wood species is correlated with features of all the trained wood images which are stored in a flat file. During the process, if the correlation value of the test image and trained image ranges between 0.75 $< r \leq 1$ approximately then, the tested image is identified to be the image present in the trained list of wood species. The images showing the value out of this range can belong to some other species. Thus the testing process is made very easy by identifying the correlation value between the test and the train image.

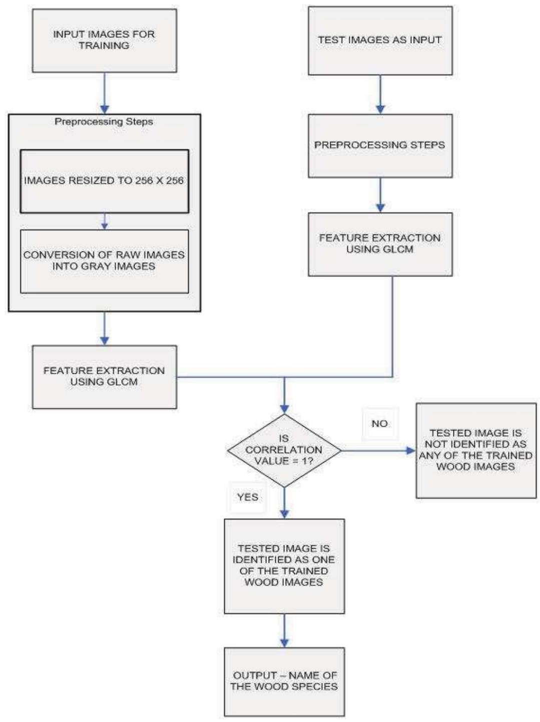


Fig. 1. A Complete Work Flow of Wood Species Recongition System

III. Wood Species Recognition

In our work, we are involved in designing a wood recognition system that can classify 10 species of Indian woods namely Burma Teak, Ebony, Oak, Padauk, Sal, Satin, Teak, White Oak and Zebra. Methodologies can be described from the following points: Data Acquisition, Feature Extraction and Classification using Correlation.

A. Wood Data Acquisition

The system has been set up to acquire the image of the wood grains using digital camera of better resolution. The usage of the digital camera is considered to be cheaper rather than using other pricey cameras. The images thus obtained are said to have the same resolution. Since, the proposed system is said identifies 10 different species of Indian Woods namely Burma Teak, Ebony, Jack, Oak, Padauk, Sal, Satin, Teak, White Oak and Zebra. Some of the acquired wood images on each wood species are shown in Figure 2

B. Wood Preliminary Operations

This module aims to improve the image to make subsequent processing easier, faster, more accurate and reliable. The preprocessing steps of the procedure involve resizing the input images to 256 * 256, and the images are converted into the

Fig. 2. Sample Indian Wood Species

gray images. A grayscale digital image is an image in which the value of each pixel is as single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at weakest intensity to white as the strongest intensity. Gray images contain the entire pixel values i.e. R, G, B values to be same.The conversion of some of the given wood images into gray images is shown in Figure 3.

C. Features of Wood Spceies

Textural analysis method is used to extract the distinct features of each wood image. From the several textural analysis methods, the Gray Level Co-occurrence Matrix (GLCM) seems appropriate. The textural information of wood is adequately specified by a set of gray tone spatial dependence Matrices, which is GLCM in this application. There are a

Fig. 3. Illustration of Wood Gray spceies Conversion

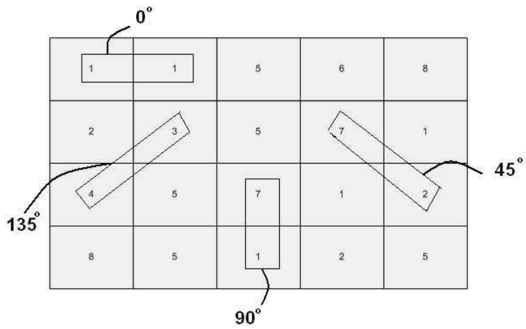


Fig. 4. GLCM's Four Orientations

total of 14 features for GLCM. Among these 14 features, 5 features are considered essential for wood classification. The essential features are Energy, Entropy, Homogeneity, Inverse Difference Moment and Angular Second Moment. The GLCM is generated by cumulating the total numbers of gray pixel pairs (offset) from the image I. Each GLCM will be generated by defining a spatial distance (distances between neighboring cell-pairs on the image) d and an orientation. For each sample of wood image, these 5 features are extracted from 4 different orientations like horizontal (0^o), vertical (90^o), and diagonals (45^o, 135^o) as shown in Figure 4. Therefore a total of 20 features are obtained from each image of wood (both training and testing images). These features are extracted for all training images of those 10 various Indian wood species. The features extracted from the input image for which the identification is about to make are correlated with the features of trained images for the classification. In reference to the GLCMs formed for the wood images, a 256 * 256 matrix is formed for each GLCM. This is because the image for which the GLCM formed is a gray image (8 bit) and the number level of the gray pixels will range from 0 - 255. The GLCMs for an image is always their number level number level of the image. Therefore the size of the GLCM would be $2^8 * 2^8$.

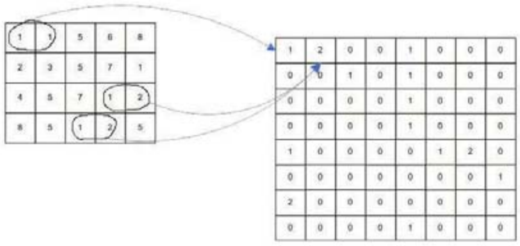


Fig. 5. Representation for 0^o orientation for GLCM

The GLCM approach can be described as follows. Consider an image whose number level is 8, which forms a GLCM of size 8 * 8. The illustration of the formation of GLCM in 0^o orientation for such an image is given in Figure 5. Equation 1 denotes an N * N image with G gray levels.

$$I(x, y), 0 \leq x \leq N-1, 0 \leq y \leq N-1 \tag{1}$$

where, x and y represent width and height of Gray image The $G * G$ gray level co-occurrence matrix P_d for a displacement vector $d = (dx, dy)$ is defined as follows. The entry (i, j) of P_d is the number of occurrences of the pair of gray levels i and j which are a distance d apart. Formally, it is given as in the Equation 2.

$$(r, s), (t, v) \epsilon N * N, (t, v) = (r + dx, s + dy) \tag{2}$$

and $|.|$ is the cardinality of a set which is explained in the Equation 3.

$$P_d(i, j) = |(r, s), (t, v)) : I(r, s) = i, I(t, v) = j| \tag{3}$$

The co-occurrence matrices are calculated from four directions, which are horizontal (0^o), vertical (90^o), and diagonal (45^o and 135^o). A new matrix is formed as the average of these matrices that is used for extracting the features. The joint probability density function normalizes the GLCM into a close approximation of the probability table by dividing every set of pixel pairs with the total number of pixel pairs used and is represented using $P(i, j)$ as shown in Equation 4.

$$P(i, j) = P_d(i, j) / \sum_{i,j=0}^{N-1} P_d(i, j) \tag{4}$$

where i is the Reference Pixel, j is the Neighbor Pixel, $P_d(i, j)$ is the Displacement Vector for (i, j) and $P(i, j)$ is the Probability Density Function.There are certain features that are extracted from these wood images from which the different species of wood can be easily classified. The textural features that are extracted are Energy, Entropy, Contrast, Angular Second Moment and Homogeneity.These features explanations are given in following sections.

1) Entropy: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy converts any class other than logical to uint8 for the histogram count calculation so that the pixel values are discrete and directly correspond to a bin value(Equation 5).

$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i, j) * \log P(i, j) \tag{5}$$

2) Energy: Energy(Equation 6) is the opposite of entropy. In that sense it represents orderliness. This is why "Energy" is used for the texture that measures order in the image. The square root of the Angular Second Moment is sometimes used as a texture measure, known as Energy.

$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i, j)^2 \tag{6}$$

3) Contrast: Contrast measure analyses the image contrast (locally gray-level variations) as the linear dependency of grey levels of neighboring pixels (similarity). Contrast is typically high, when the scale of local texture is larger than the distance(Equation 7).

$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 * P(i, j) \tag{7}$$

4) Angular Second Moment: Angular Second Moment is also known as Uniformity. This is a measure of local homogeneity and the opposite of Entropy. High values of Angular Second Moment occur when the pixels in the moving window are very similar.

5) Homogeneity: Homogeneity is the most commonly used measure that increases with less contrast in the pixel. Dissimilarity and Contrast result in larger numbers for more contrast pixels. If weights decrease away from the diagonal, the result will be larger for pixels with little contrast. Homogeneity weights values by the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal(Equation 8).

$$\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i, j) / 1 + (i - j)^2 \tag{8}$$

Table I represents the average value of the features extracted from all the training images of particular wood species. These values are extracted using the GLCMs formed at 0^o Orientation. This forms the first set of 5 Features.

Figure 6 represents the values of all 5 features extracted at 0^o orientation. These represented 5 features of a particular species are the average of the features extracted from all the trained images of the same species.

Table II represents the average value of the features extracted from all the training images of particular wood species. These values are extracted using the GLCMs formed at 90^o Orientation. This forms the next set of 5 features. Figure 7 represents the values of all 5 features extracted at 90^o orientation.

Table III represents the average value of the features extracted from all the training images of particular wood species. These values are extracted using the GLCMs formed at 45^o Orientation. This forms the next set of 5 features.Figure 8 represents the values of all 5 features extracted at 45^o orientation. Table IV represents the average value of the features

TABLE I
FEATURE EXTRACTION ON 0^o ORIENTATION

Woods Types	Entropy	Energy	Contrast
Burma Teak	0.41	$2.7*10^{-3}$	$2.7*10^{-4}$
Ebony	0.82	$3.34*10^{-3}$	$1.3*10^{-4}$
Oak	0.1	$3.45*10^{-3}$	$1.3*10^{-4}$
Sal	2.12	$55.53*10^{-3}$	8.9
Satin	0.39	$2.58*10^{-3}$	$5*10^{-4}$
Teak	0.63	$3*10^{-3}$	$2.64*10^{-4}$
Zebr	0.89	$3.25*10^{-3}$	$1.25*10^{-4}$

Woods Types	Angular Second Moment	Homogeneity
Burma Teak	$3.05*10^7$	$53.7*10^3$
Ebony	$3.4*10^{-4}$	$366.1*10^3$
Oak	$9.675*10^8$	$775*10^3$
Sal	$3.91*10^7$	$103*10^3$
Satin	$2.95*10^7$	$43.5*10^3$
Teak	$2.009*10^8$	$193.8*10^3$
Zebr	$1.42*10^9$	$814.5*10^3$

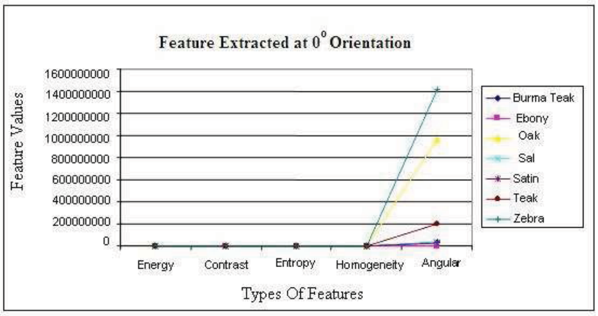


Fig. 6. Representation of the Features Values Vs Types of features at 0^o Orientation

TABLE II
FEATURE EXTRACTION ON 90^o ORIENTATION

Woods Types	Entropy	Energy	Contrast
Burma Teak	0.33	$2.5*10^{-3}$	$4.3*10^{-4}$
Ebony	0.65	$2.97*10^{-3}$	$2.1*10^{-4}$
Oak	0.77	$3.06*10^{-3}$	$2.2*10^{-4}$
Sal	1.88	$44.37*10^{-3}$	$0.1*10^{-4}$
Satin	0.35	$2.27*10^{-3}$	$7.2*10^{-4}$
Teak	0.54	$2*10^{-3}$	$4.63*10^{-4}$
Zebr	0.72	$2.7*10^{-3}$	$2.97*10^{-4}$

Woods Types	Angular Second Moment	Homogeneity
Burma Teak	$23*10^7$	$39.40*10^3$
Ebony	$3.04*10^8$	$277.48*10^3$
Oak	$7.09*10^8$	$559.48*10^3$
Sal	$3.11*10^7$	$91.30*10^3$
Satin	$2.55*10^7$	$38.09*10^3$
Teak	$1.60*10^8$	$159.01*10^3$
Zebr	$9.5*10^8$	$574.40*10^3$

extracted from all the training images of particular wood species. These values are extracted using the GLCMs formed at 135^o Orientation. This forms the last set of 5 features. Figure 9 represents the values of all 5 features extracted at 135^o orientation.

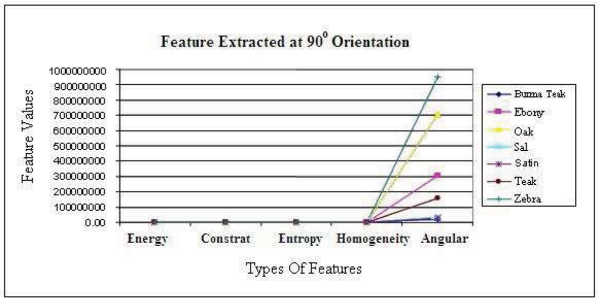


Fig. 7. Representation of the Features Values Vs Types of features at 90^o Orientation

TABLE III
FEATURE EXTRACTION ON 45^o ORIENTATION

Woods Types	Entropy	Energy	Contrast
Burma Teak	0.56	0.00	$2.3*10^{-4}$
Ebony	1.09	0.01	$1*10^{-4}$
Oak	1.29	0.01	$1.3*10^{-4}$
Sal	2.36	0.07	$0.01*10^{-4}$
Satin	0.37	0.00	$5.049*10^{-4}$
Teak	0.58	0.00	$3.42*10^{-4}$
Zebr	0.78	0.00	$2.39*10^{-4}$

Woods Types	Angular Second Moment	Homogeneity
Burma Teak	$4.224*10^7$	$61.92*10^3$
Ebony	$5.8*10^8$	$471.80*10^3$
Oak	$1.303*10^9$	$942.45*10^3$
Sal	$5.55*10^7$	$120.84*10^3$
Satin	$2.8*10^7$	$40.80*10^3$
Teak	$1.824*10^8$	$176.07*10^3$
Zebra	$1.08*10^9$	$634.45*10^3$

D. *Classification using Correlation*

The Correlation texture measures the linear dependency of grey levels on those of neighboring pixels. The correlation is a measure of association (resemblance) between two images to find those portions that match according to the measure of correlation. From the extracted features we compare the images by using Pearson correlation technique. In statistics, the Pearson product-moment correlation coefficient (sometimes referred to as the MCV or PMCC, and typically denoted by r) is a common measure of the correlation (linear dependence)

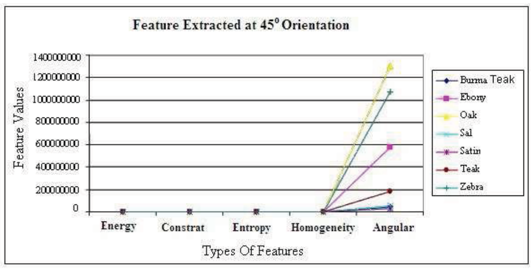


Fig. 8. Representation of the Features Values Vs Types of features at 45^o Orientation

TABLE IV
FEATURE EXTRACTION ON 135^o ORIENTATION

Woods Types	Entropy	Energy	Contrast	Angular Second Moment	Homogeneity
Burma Teak	0.31	$2.3*10^{-3}$	$5*10^{-4}$	$2.2*10^{7}$	$37.28*10^{3}$
Ebony	0.62	$2.8*10^{-3}$	$2*10^{-4}$	$8.47*10^{7}$	$272.28*10^{3}$
Oak	0.74	$2.9*10^{-3}$	$2*10^{-4}$	$6.99*10^{8}$	$550.86*10^{3}$
Sal	1.87	$43.1*10^{-3}$	0.00	$3.02*10^{7}$	$90.37*10^{3}$
Satin	0.29	$1.9*10^{-3}$	$9*10^{-4}$	$2.14*10^{7}$	$31.89*10^{3}$
Teak	0.46	$2.2*10^{-3}$	$5*10^{-4}$	$1.45*10^{8}$	$142.12*10^{3}$
Zebr	0.63	$2.4*10^{-3}$	$3*10^{-4}$	$9.035*10^{8}$	$539.01*10^{3}$

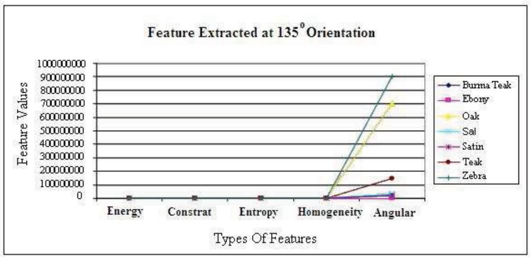


Fig. 9. Representation of the Features Values Vs Types of features at 135^o Orientation

between two variables X and Y. It is very widely used in the sciences as a measure of the strength of linear dependence between two variables, giving a value somewhere between +1 and -1 inclusive. It was first introduced by Francis Galton in the 1880s, and named after Karl Pearson. If two images are same then the correlation value = 1. The formula used to find the correlation value is given in the Equation 9

$$R = \frac{\sum(x - Avg(x)) * (y - Avg(y))}{\sqrt{\sum(x - Avg(x)^2 * \sum(y - Avg(y))}} \tag{9}$$

where,R is a Correlation factor,x represents Features of Trained wood Image and Y represents Features of Testing Image If both images are identical then R will be 1.

IV. IMPLEMENTATION AND RESULT ANALYSIS

The main objective of this system is to recognize the species of wood, which is, give as the input to the system. At the outset as discussed, the proposed system is trained with the 10 Indian wood species. Some images from each species are trained to the system and the features of all the images that are trained are saved in a flat file, which is used for the classification of test image. Figure 10 illustrates the input and resize of such a wood image. The images are resized automatically to the size 256 * 256 when they are loaded. The next step of the training process is to convert the loaded color image to gray

Fig. 10. Training process of wood Images

image. From these Gray images we then extract features using GLCM Algorithm. GLCMs are formed for all the training images. Each image will have 4 GLCMs, i.e. a GLCM for each of the four orientations. From these gray images using the method of GLCM matrices are formed for 4 orientations from which necessary features are extracted for classification. The extracted 20 features of these training images are then stored as .txt file, which will be used for comparison. Only after training the images, the system allows the user to test a new image. The test image is then preprocessed, converted into gray and undergoes features extraction. These features are compared with stored features of trained images features by the correlation method and finally depending on the correlation value, the species of the input wood image is concluded. If the correlation value of the testing image and any of the trained images is 1, then the trained and tested images are just the same and the species of the tested image is declared as the species of the trained image. Else the highest correlated value in testing process is checked for, comparing with all the correlation values obtained with all the trained images. Finally the species of the tested image is declared as the species of the trained image with which the correlation value was the greatest. Else if the correlation value between the test image and any of the training images doesn't reach the range ($0.75 < r = 1$), the species of the test image is declared unknown, i.e. the wood species that is not trained to the proposed system. Figure 11 illustrates the testing process of a loaded image. It displays the image loaded for testing and the average correlation values of each species of wood. Since the correlation value of the tested image and the Satin images is higher, the loaded image is declared as SATIN WOOD. The list of name of the wood species and the correlation values at the testing process are tabulated(Table V). Since the correlation value for the testing image and the Satin species is the highest, the name of the species of the loaded image is declared as SATIN.The graphical representation of the species and the corresponding correlation values are represented in Figure 12.

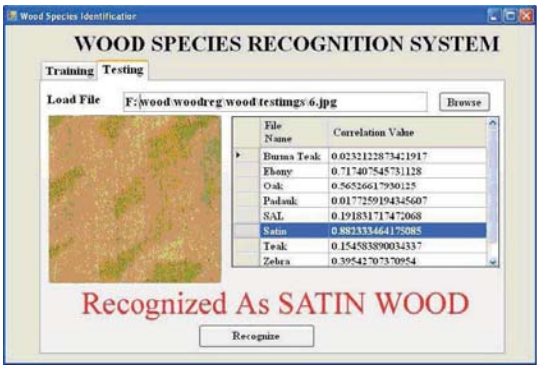


Fig. 11. Recognition Process of wood Images(Satin Wood is identified in testing)

TABLE V
LIST OF WOOD SPECIES AND ITS CORRELATION VALUES DURING TESTING

Wood Species	Correlation value
Burma Teak	0.02321
Ebony	0.7174
Oak	0.5652
Padauk	0.0177
Sal	0.1918
Satin	0.8823
Teak	0.1545
Zebr	0.3954

V. CONCLUSION

Thus a visual inspection system for the recognition of he wood is developed. The system was objectively designed to be cost-effective and as a means to replace wood inspectors due to difficulty in recruiting them as workers which is rather laborious. The system shows an effectual visualization of the application. The image processing techniques are applied to improve the image excellence. In this design we have applied GLCM approach to extract the features from the digital wood images. This GLCM algorithm is robust to rotation such that the wood images can be captured at any orientation of same resolution. The correlation is the technique used for the classification of the wood species. The system shows a high rate of accuracy of recognizing 10 different Indian wood species.

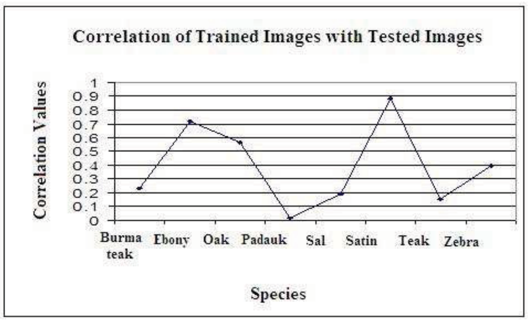


Fig. 12. Wood Species and its Correlation Values for Testing Process process

ACKNOWLEDGMENT

Authors thank the SNR & Sons Charitable trust,Coimbatore,India for providing necessary infrastructure to complete this research study.

REFERENCES

[1] Marzuki Khalid, *Design of an Intelligent Wood Species Recognition System*, Center for Artificial Intelligence and Robotics (CAIRO), Malaysia, 2008.

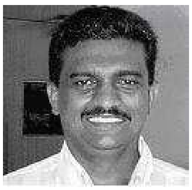
[2] R. Jordan, *Classification of Wood Species by Neural Network Analysis of Ultrasonic Signals*, Ultrasonic 36(1-5), pp. 219-222, 1998.

[3] J. Lampinen and S. Somlander, *Self Organizing Feature Extraction in Recognition of Wood Surface Defects and Color Images*, International Journal of Pattern Recognition and Artificial Intelligence, 1996.

[4] H. Kauppinen, *Development of a Color Machine Vision Method for Wood Surface Inspection*, Ph.D Thesis, Department of Electrical Engineering, University of Oulu, 1999.

[5] Brandtberg, *An Wood Identification System, that classify individual tree crown into respective wood species*, 2002.

[6] Jing Yi Tou, Yong Haur Tay and Phooi Yee Lau, *Gabor Filter and Gray-level Co-Occurrence Matrices In Texture Classification*, Computer Vision and Intelligent System (CVIS) Group, Faculty of Information and Communication Technology, University Tunku Abdul Rahman (UTAR), Malaysia, 2002.



Bremananth R received the B.Sc and M.Sc. degrees in Computer Science from Madurai kamaraj and Bharathidsan University, India in 1991 and 1993, respectively. He has obtained M.Phil. degree in Computer Science and Engineering from Bharathiar University. He has received his Ph.D. degree in the Department of CSE, PSG College of Technology, India, Anna University, Chennai. Presently, he is a Professor, Department of Computer Applications, Sri Ramakrishna Engineering College, Coimbatore. He has 16 years of teaching experience and published several research papers in the National and International Journals and Conferences. He has received M N Saha Memorial award for the year 2006 by IETE. His fields of research are pattern recognition, computer vision, image processing, biometrics, multimedia and soft computing.

Dr. Bremananth is a member of Indian society of technical education(ISTE), advanced computing society(ACS), Institute of Electronics and Telecommunication Engineers(IETE) and WASET.

Nithya B. Nithya has received Bachelor degree in Computer Technology from Sri Ramakrishna Engineering College, Anna University, Chennai. She is a student application developer at Wipro Technologies, India.

Saipriya R. Saipriya has received Bachelor degree in Computer Technology from Sri Ramakrishna Engineering College, Anna University, Chennai. She is a student application developer at Wipro Info Tech, India.