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Multiresolution local binary pattern variants based texture feature extraction techniques for efficient classification of microscopic images of hardwood species

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ABSTRACT

In this paper, multiresolution local binary pattern (MRLBP) variants based texture feature extraction techniques have been proposed to categorize hardwood species into its various classes. Initially, discrete wavelet transform (DWT) has been used to decompose each image up to 7 levels using Daubechies wavelet (db2) as decomposition filter. Subsequently, six texture feature extraction techniques (local binary pattern and its variants) are employed to obtain substantial features of these images at different levels. Three classifiers, namely, linear discriminant analysis (LDA), linear and radial basis function (RBF) kernel support vector machine (SVM), have been used to classify the images of hardwood species. Thereafter, classification results obtained from conventional and MRLBP variants based texture feature extraction techniques with different classifiers have been compared. For 10-fold cross validation approach, texture features acquired using discrete wavelet transform based uniform completed local binary pattern ($DWTCLBP^{u2}$) feature extraction technique has produced best classification accuracy of $97.40 \pm 1.06\%$ with linear SVM classifier. This classification accuracy has been achieved at the 3rd level of image decomposition using full feature (1416) dataset. Further, reduction in dimension of texture features (325 features) by principal component analysis (PCA) has been done and the best classification accuracy of $97.87 \pm 0.82\%$ for $DWTCLBP^{u2}$ at the 3rd level of image decomposition has been obtained using LDA classifier. The $DWTCLBP^{u2}$ texture features have also established superiority among the MRLBP techniques with reduced dimension features for randomly divided database into fix training and testing ratios.

1. Introduction

Wood is considered to be one of the nature's supreme souvenirs for mankind. Wood has drawn attention of art historians, archeologists, forensic and paleontologists, and all living things on this earth for centuries [1]. Wood is by and large classified into hardwood (HW) and softwood (SW) species. Softwood trees (Gymnosperms) have scale-like foliage and are not deciduous. It has a simple cellular structure and 90% to 95% of the cells are longitudinal tracheids. Because of a limited number of cell types, it turns out to be difficult task to discriminate softwood species from one another [2]. On the other hand, hardwood species originate from Angiosperm trees. Unlike their counterparts, hardwood species have a complex cellular structure and are easy to distinguish among the similar species. Vessels, fibers, parenchyma's and rays are the four major elements useful in the identification of hardwood species. Vessels, also known as pores (in cross-section view) are the missing elements in softwood species. Correct identification of wood species is crucial for many reasons, especially to strengthen the endeavor to fight against the illegal logging and smuggling of precious woods, and protection of threatened plant and tree species at risk. It would also help custom officials to properly assess the wood species and then implement tariffs accordingly [1]. Like humans, unique cellular structure of the wood species (which vary among the intra-species) acts as a blueprint for its identification [2].

Traditionally, the hardwood identification is being carried out by a small number of skilled officers using macroscopic image textures, weight, aroma and the color of the wood specimen [1]. Microstructures of hardwood cross-section samples are used for the identification of wood species, wherein the features of unknown samples of hardwood species are compared with the features of available samples [3].

The major challenge in wood identification is the non-availability of infrastructure (xylarium, microslides and literature for comparing the microstructure of unknown wood sample with the known) and the scarcity of highly skilled manpower with proven experience in the said field. Further, imparting training to human officers to attain an expertise in identification of wood is a time-consuming process. Nowadays, occupation as a wood certification officer is neither easy nor lucrative and likelihood of unfairness and oversight cannot be denied. Moreover, identification of large quantity of wood samples is not only time consuming, but also erroneous and impractical to implement in real world applications. There is no systematic classification procedure for wood identification and, thus, a specie has to be identified based on the combination of its microstructure features. In tropical countries there is huge hardwood diversity. India alone has over 1200 hardwood species and, therefore, memorizing the microstructure of all the species is next to impossible. Thus, to effectively address the above said issues researchers are looking into the possibility

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Table 1
Forest species classification approach summary.

Refs.	Image (database)	No of images (categories)	Texture features	Classifiers	Classification accuracy
Tou et al. [5]	Macroscopic (CAIRO)	360 (5)	GLCM (4 features)	MLP-ANN	72%
Khalid et al. [6]	Macroscopic (FRIM)	1949 (20)	GLCM (5 features in 4 directions)	MLP-BP-ANN	95%
Wang et al. [7]	Stereogram	480 (24)	GLCM (6 features in 4 directions)	SVM, NN	91.70%
Wang et al. [8]	Stereogram	480 (24)	Mean, SD, contrast and entropy calculated on Gabor images	NN	94.58 ± 1.84%
Martins et al. [9]	Microscopic	2240 (112) SW (37), HW (75)	GLCM, structural, LBP	SVM, KNN, LDA	86.00%
Cavalin et al. [10]	Microscopic	2240 (112) SW (37), HW (75)	GLCM, LBP, LPQ	SVM	93.20%
Yosuf et al. [11]	Macroscopic (FRIM)	5200 (52)	Kernel genetic algorithm	LDA	98.69%
Yosuf et al. [12]	Macroscopic (FRIM)	5200 (52)	BGLAM, SPPD, fuzzy logic as pre-classifier	LDA, KNN, MLP-ANN	93.00%
Ahmad et al. [13]	Macroscopic (FRIM)	5040 (52)	BGLAM, SPPD	ACA	96.75%
Wang et al. [14]	Stereogram (ZAFU WS24)	480 (24)	Mask matching image (MMI)	KNN, SVM	87.67 ± 2.01%
Wang et al. [15]	Stereogram	480 (24)	Mean, SD, entropy, variance, energy and dissimilarity features from 40 Gabor patterns of original image	LOOCV, NN	97.30%
Yadav et al. [16]	Microscopic	500 (25), HW	GLCM and Gabor wavelet	MLP-BP-ANN	92.60%
Yadav et al. [17]	Microscopic	500 (25), HW	DWT based mean, SD, kurtosis and skewness	MLP-BP-ANN	92.20%
Paula et al. [18]	Macroscopic	2942 (41)	Color features, GLCM, Gabor filters, LBP, fractals, edge histograms, LPQ, CLBP	SVM	97.77%

SW – softwood; HW – hardwood; GLCM – gray level co-occurrence matrix; SD – standard deviation; LBP – local binary pattern; LPQ – local phase quantization; BGLAM – basic gray level aura matrix; SPPD – statistical properties of pores distribution; CLBP – completed local binary pattern; MLP – multilayer perceptron; BP – backpropagation; ANN – artificial neural network; SVM – support vector machine; NN – nearest neighbor; KNN – *k* nearest neighbor; LDA – linear discriminant analysis; ACA – ant clustering algorithm; LOOCV – leave one out cross validation.

of coming up with computer assisted forest species/hardwood species identification system.

The limitations of the traditional techniques have opened the new way for wood identification which is machine vision based. This has been the first motivation for this task. The core goal of machine vision based identification system in the context of wood identification is to achieve quantifiable, repeatable and reliable pattern recognition results [4]. The machine vision based forest/hardwood species identification techniques were introduced by several researchers [5–18]. These techniques have shown ability in performing the task with reasonable accuracy based on the statistical information (texture features) extracted from the images of various wood species [5–18]. The summary of the forest species classification based on the texture features of macroscopic, microscopic and stereogram images are listed in Table 1. From the summary given in Table 1, it is seen that texture features in combination with classifiers have produced reasonably better classification accuracy for forest/hardwood species.

The microscopic images of wood provide sufficient information for accurate classification of variety of woods in contrast to macroscopic images that reveal only limited amount of information [19]. Taking into account the results and discussion provided by various authors in the available literature [5–18] on classification of wood images, it is understood that the recognition accuracy, can be improved by employing a suitable texture feature descriptor for acquiring significant texture information of an image. This has been the second motivating point for the present work. As the coarse resolution to fine resolution approach is effectively used for pattern recognition approaches [20], the wavelet transform has been used for feature extraction [21]. The intrinsic multiresolution ability of DWT makes it an exceptional tool for feature extraction and analysis of an image. In the above perspective, in the present work, a multiresolution local binary pattern (MRLBP) variants based texture feature extraction techniques for microscopic images of hardwood species has been proposed. This technique puts together multiresolution capability of DWT, and variants of LBP. Further, three supervised classifiers are employed to investigate the effectiveness of the texture feature extraction techniques on microscopic images of hardwood species.

The contents of the present research paper are structured as follows: Section 2 discusses in detail the proposed methodology for classification of hardwood species using MRLBP variants based texture features. The comprehensive review of DWT, LBP variants and three classifiers is presented in Section 3. Section 4 brings out a critical discussion on experimental result and the performance evaluation of the proposed texture feature extraction techniques. The work is concluded in Section 5.

2. Proposed methodology

The procedure for the classification of microscopic images of hardwood species is shown in Fig. 1. The four major steps involved to accomplish hardwood species classification task are preprocessing, texture feature extraction, feature dimension reduction and classifier. The microscopic images are added with color information to enhance certain anatomical features of hardwood species. Thus, the preprocessing step is involved to obtain grayscale image from color (RGB) image, which results in significant reduction of computational time during texture feature extraction.

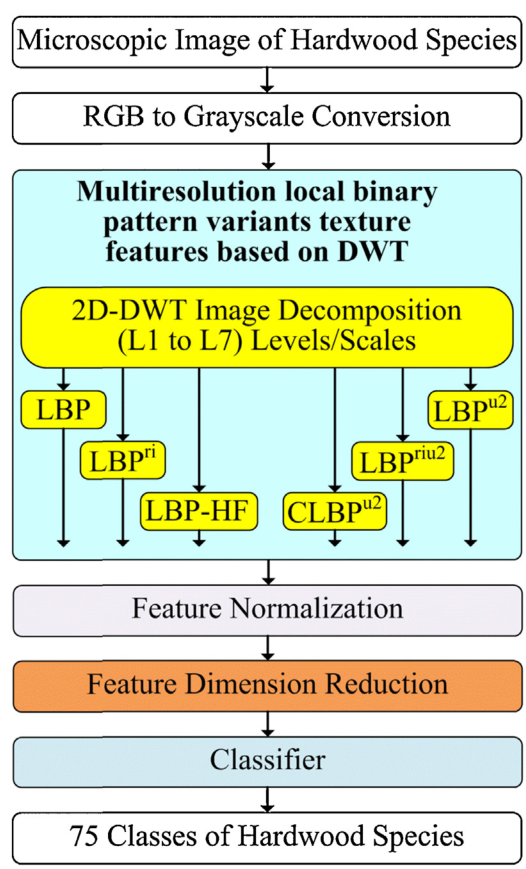

Fig. 1. Block diagram of proposed multiresolution local binary pattern (MRLBP) variants based texture features for hardwood species classification.