STATISTICAL PROPERTIES OF LINES DISTRIBUTION FOR TROPICAL WOOD RECOGNITION SYSTEM

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DEDICATION

This thesis is dedicated to my family, who have been my source of inspiration and gave strength and provide financial support to finish this study. To my lab mates who shared their word of advice and encouragement. Thank you for all your support along the way.

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ABSTRACT

An automated tropical wood recognition system has been developed by Centre for Artificial Intelligence & Robotics (CAIRO), Universiti Teknologi Malaysia (UTM) based on machine vision to emulate the experts known as KenalKayu. The system used Statistical Properties of Pores Distribution (SPPD) feature extractor and K-Nearest Neighbor (KNN) classifier which have been proven to increase the system's accuracy. Unfortunately, when more wood species were added to the system's database, it reduces the accuracy of the system. Therefore, providing additional features that are representation of each species is one way to improve this issue. As the wood surface pattern is not only defined by pores but lines as well, this thesis presents additional new feature extraction method based on Statistical Properties of Line Distribution (SPLD) to capture the discriminant line features of each species and K-Nearest Neighbor (KNN) is used as classifier. The results of experiments showed that when used by itself as a feature extractor, the SPLD managed to achieve 88% accuracy, and the accuracy increased to 99.5% when combined with SPPD features and 100% accuracy was achieved when SPPD and Basic Grey Level Aura Matrix (BGLAM) features were used in combination. In conclusion, the SPLD method is an essential customized feature extractor and could be used as an alternative to adequately identify wood species. Hence, in the future, other discriminant features can also be added for wood identification purposes.

ABSTRAK

Sistem pengecaman kayu tropika automatik telah dibangunkan oleh Pusat Kecerdasan Buatan & Robotik (CAIRO), Universiti Teknologi Malaysia (UTM) berdasarkan visi mesin untuk mencontohi pakar yang dikenali sebagai KenalKayu. Sistem ini menggunakan pengekstrak ciri Sifat Statistik Taburan Liang (SPPD) dan pengelas Kejiranan Terdekat-K (KNN) yang telah terbukti meningkatkan ketepatan sistem. Malangnya, apabila lebih banyak spesies kayu ditambahkan pada pangkalan data sistem, ia mengurangkan ketepatan sistem. Oleh itu, menyediakan ciri tambahan yang mewakili setiap spesies adalah satu cara untuk memperbaiki isu ini. Memandangkan corak permukaan kayu bukan sahaja ditakrifkan oleh liang tetapi garisan juga, tesis ini membentangkan kaedah pengekstrakan ciri baharu tambahan berdasarkan Sifat Statistik Taburan Garis (SPLD) untuk mengenal pasti ciri garis diskriminasi setiap spesies dan Kejiranan Terdekat-K (KNN) digunakan sebagai pengelas. Keputusan eksperimen menunjukkan bahawa jika ianya digunakan dengan sendiri sebagai pengekstrak ciri, SPLD berjaya mencapai ketepatan 88%, dan ketepatan tersebut meningkat kepada 99.5% apabila digabungkan dengan ciri SPPD manakala ketepatan 100% dicapai apabila SPPD dan Matrik Aura Aras Kelabu Asas (BGLAM) digunakan secara gabungan. Kesimpulannya, kaedah SPLD adalah pengekstrak ciri khas yang penting dan boleh digunakan sebagai alternatif untuk mengenal pasti spesies kayu. Oleh itu, pada masa hadapan, ciri-ciri diskriminasi lain juga boleh ditambah untuk tujuan pengecaman kayu.

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LIST OF ABBREVIATIONS

AIKO	-	Automatic wood identification tool
BGLAM	-	Basic Grey Level Aura Matrix
BPNN	-	Back propagation neural network
CAIRO	-	Centre for Artificial Intelligence and Robotics
CCD	-	Charge-coupled device
FN	-	False negative
FP	-	False Positive
FRIM	-	Forest Research Institute of Malaysia
GA	-	Genetic Algorithm
GG	-	Gestaltic Grouping
GLCM	-	Grey level co-occurrence matrix
GMRF	-	Gaussian Markov random field
HT	-	Hough Transform
KDA	-	Kernel Discriminant Analysis
KNN	-	K-Nearest Neighbor
KSOM	-	Kohonen Self-Organizing Map
LBP	-	Local Binary Pattern
LDA	-	Linear Discriminant Analysis
LSD	-	Line Segment Detector
MTIB	-	Malaysia Timber Industry Board
MV	-	Machine vision
NFA	-	Number of false alarms
NLA	-	Non-local alignments
SPLD	-	Statistical Properties of Lines Distribution
SPPD	-	Statistical Properties of Pores Distribution
TN	-	True Negative
TP	-	True Positive
UTM	-	Universiti Teknologi Malaysia
VSDP	-	Vision System Development Platform

LIST OF SYMBOLS

ρ	-	Maximum distance between the origin and the line tip
θ	-	Maximum acceptable angle
$\Delta\theta$	-	An angle threshold parameter
$\Im^{\rho}$	-	NFA of parallel line event
$\varsigma^{k,\rho}$	-	NFA of non - local alignment
$\wp^{k,\rho,\theta}$	-	NFA of good continuation
N	-	Total number of line segment
K	-	Maximum number of line segments in a good continuation

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

For a long time, tropical rainforests have been regarded as one of the world's most productive forest. In this world, the tropical rainforests can only be found in South America, Central Africa and Southeast Asia. Malaysia is located in South East Asia and a home to over 2,650 tree species, with natural forest occupying more than 55.3 percent of its land area. According to Malaysia Timber Industry Board (MTIB), since June 2019, Malaysia has 4.34 million hectares of certified forests endorsed by the Program for the Endorsement of Forest Certification scheme to fulfill the demand for certified timber products [1]. Malaysia forests provide a large variety of useful materials, ranging from medicinal plants and food to fiber and timber [2].

Furthermore, Malaysia is one of the world's top tropical timber producers and top 10 furniture producers. The timber industry is an important contributor to the Malaysian economy. In 2019, Malaysia earned RM 22.5 billion from timber exports [3]. In fact, Malaysian timber currently shipped to more than 162 countries, with India being the major importer. However, deforestation is a critical threat as the country is still developing. Some timber traders tend to mix different types of wood and even try to export an endangered wood species to increase their profit margin. Nevertheless, the remaining forests face challenges from unsustainable logging, illegal removal of forest resources and encroachment [4]. Various measures have been proposed to combat this problem including wood identification by wood experts at various checkpoints.

It is easy to identify a tree by observing its flowers, fruits and leaves. However, once the tree is cut down and become wooden logs, it becomes very difficult to identify the tree species and the expert must rely on their physical characteristics for species identification. Wood species has different appearances such as shapes, smells, odor and colors of the leaves. These characteristics are called macroscopic features and can be used to indicate whether a wood is labeled correctly, or to which species it is likely to belong to. Recent wood can often be identified by macroscopic characteristics, particularly by color, gloss, odor, weight and structure. As such characteristics are generally modified or destroyed in fossil, historic or carbonized wood, only a few species or species groups of the indigenous flora can be identified with the naked eye or only with the aid of a magnifier (5 to 20x). Macroscopic keys typically have fewer features than microscopic keys. Several species have identical macroscopic features and therefore, for identification, it is more reliable to use microscopic characters instead of macroscopic features [5].

The microscopic features on wood cross sectional surfaces are useful for identification and determining the wood species because different kind of wood species will have a distinctive microscopic feature. Macroscopic features are usually generic whereas microscopic features necessitate a more thorough anatomical inspection with the aid of IAWA List of Microscopic Features for Hardwood Identification [5]. The anatomical features in this list composed of growth rings, porosity, vessel arrangement, vessel groupings, outline of solitary vessels, perforation plate type, intervessel pit arrangement and size, type of fiber wall pitting, fiber wall thickness and length, axial parenchyma distribution, ray width, aggregate rays, cellular composition of rays, storied structure, intercellular canals and their cellular location.

The wood detection and classification process are currently performed manually by wood experts with handheld lens or unaided eye [6]. A dichotomous key [7] is provided as a guideline for the experts to determine the wood species. However, the conventional technique in performing wood identification can lead to difficulties in using keys due to errors in recognizing feature. In addition, lack of background or training in wood identification can lead to a feature being misinterpreted. Apart from that, a feature may also be interpreted differently from the way a key constructor intended. Fault in recognizing a feature is likely to be a cause of misidentification of the wood species.

Wood recognition is mainly done by well-trained wood experts. Regrettably, it takes a long period of time to train a wood expert which is qualified to identify wood species with high accuracy because there are more than 3000 wood species in Malaysia. The process of examining every unit of wood by a human inspector can be tedious and time consuming. There will also be a problem in identifying the timber accurately especially the lesser-known species. Wood experts are not abundant in the market today to meet the demand in the industry which involves in raw wood identification.

Therefore, it may not be feasible if the customs need to check and identify the species of wood before they are exported out of the country. Manufacturers can also use the technique to check and verify whether the wood materials acquired are from the correct species, as different type of wood species will have different value, verification of the species is important to avoid unnecessary loss for the manufacturers. In view of these factors, a systematic method is essential so that the identification of wood species can be carried out quickly and accurately.

To mitigate this problem, an automated visual inspection may help users to recognize wood species in just an instant. It has been implemented to a variety of applications and has been used for century to replace humans with intelligent machines in different industries. Centre for Artificial Intelligence and Robotics (CAIRO), Universiti Teknologi Malaysia (UTM) in particular Khalid et al. [8] had developed a tropical wood recognition system based on wood macroscopic anatomy called KenalKayu. The research has been done since 2002 and it has been improved in so many ways just to ensure the system is able to recognize the wood species. This system may replace the conventional technique in performing wood identification which is exposed to human error and biasedness.

1.2 Problem Statement

The main problem in wood recognition system is the lack of discriminative features of the texture image and also very discriminative features among inter class species [9] as well as noises due to illuminations, or uncontrolled environment. Some of the wood species have similar pattern with other and some have different pattern even though they are from the same species. So, there is a need on how to develop more accurate algorithm for wood species recognition based on texture analysis. Usually, the wood experts do this process manually and they used dichotomous key [10] which is the traditional way to classify the wood species by looking at the tree barks and the pattern of the wood cross-section. The wood features such as the size of pores, the density of pores, etc. depends very much on the age, weather and other factors, contributing to the irregularities of the features. Due to these factors, classification of the wood species remains a challenging task.

Many studies have been done in area of wood recognition system. Researchers like [8], [9], [11]–[14] had been working on automated tropical wood recognition to improve the system. The work includes the use of grey level co-occurrence matrix (GLCM) technique for extracting the texture features of the wood species and using back propagation neural network (BPNN) for classification. Yusof et al. [15] adopted fusion of two feature sets using multi feature extractor technique. Two feature extraction methods were used in this system is grey level co-occurrence matrix approach (GLCM) and Gabor filters. Khalid et al. [16] has developed a pre-classification stage to solve the problem of nonlinearity of tropical wood species separation boundaries using K-Means Clustering and Kernel Discriminant Analysis (KDA).

In later development, Khairuddin et al. [12] introduced Genetic Algorithm (GA) as feature selection 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. Their work showcased an improved automated tropical wood recognition system that can perform accurate wood identification for 70 wood databases in an offline mode. Unfortunately, when more woods were added in the database, or when the testing was done online with new wood images, the accuracy of the system drops.

It is worth taking a step back and looks at how experts identify the wood in manual ways using the dichotomous keys. As features of wood rely heavily on pores characteristics, Khairuddin et al. [12] proposed a new feature extraction method specifically for tropical wood called the Statistical Properties of Pores Distribution (SPPD). The feature extraction mimics manual procedure of tropical wood species recognition which is observing the pores characteristics such as size and density of pores. The SPPD feature extractors managed to increase the system's accuracy.

However, the SPPD method ignores another very important wood microscopic feature that are used by experts in the dichotomous key, the line characteristics. As we know, the most prevailing features that were usually used by experts to examine wood species are by looking at lines thickness, lines length and whether the lines are continuous or cut into several short lines, parenchyma lines or ray lines. Some of the wood does not have any lines at all. This shows that lines feature in wood cross sectional surface may be the key or important features that should be added in the automated wood recognition system.

1.3 Research Objective

The prototype of the intelligent tropical wood recognition had successfully been developed but the system performances need to be improved for the industrial use. The objectives of this thesis are as follows:

(a) To develop a new feature extraction method for automated tropical wood recognition system based on the line properties and distribution using Gestaltic Grouping of Line Segments detection algorithm.

(b) To evaluate and validate the newly developed line feature extraction method for automated tropical wood species identification.

(c) To determine the most effective features extractor that provides the highest accuracy during classification in automatically recognizing the wood species.

1.4 Research Scope

The scopes of this research are as follows:

(a) The proposed method will be trained and tested using images from 20 wood species that were taken using the new microscopic camera. Two databases will be used in this research which are Database A1 and Database A2.

(b) Several algorithms are used for development of the system such as a contrario model is used for detecting the line segment, SPLD as a feature extraction and K-Nearest Neighbor (KNN) as a classifier.

(c) The recognition of the tropical wood species focuses on wood species in Malaysia only and based on the wood anatomy images.

(d) Input images are all in grayscale because the macroscopic wood classification does not rely on the wood colour.

1.5 Thesis Contribution

The major contributions described in this thesis are as follows:

(a) A novel feature extraction method based on wood microscopic line features namely Statistical Properties of Line Distribution (SPLD) technique to capture the discriminant line features of each species.

(b) Finding the best combination of feature extraction methods including the new line-based features for accurate tropical wood species identification.

1.6 Thesis Outline

This thesis is organized into five chapters described as follows:

(a) Chapter 1 introduces background information and problem on the tropical wood identification. It also consists of the scopes and objectives, contributions, and outline of the thesis.

(b) Chapter 2 provides a critical review on the specific topics of wood recognition based on anatomical features, previous research on automated wood species identification and literature review on line extraction.

(c) Chapter 3 explains the methodologies and research flow adopted in this study starting from the data acquisition, image processing, feature extraction and classifier techniques used.

(d) Chapter 4 presents the results and discussion of the experiments conducted using the proposed methodologies described in Chapter 3. A critical analysis of the finding is also presented.

(e) Chapter 5 presents the conclusion of this research, the limitation of study and the recommended future works that can improve upon the findings.

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