METHOD FOR SOLVING NONLINEARITY IN RECOGNISING TROPICAL WOOD SPECIES

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To my beloved husband and daughter

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ABSTRACT

Classifying tropical wood species pose a considerable economic challenge and failure to classify the wood species accurately can have significant effects on timber industries. Hence, an automatic tropical wood species recognition system was developed at Centre for Artificial Intelligence and Robotics (CAIRO), Universiti Teknologi Malaysia. The system classifies wood species based on texture analysis whereby wood surface images are captured and wood features are extracted from these images which will be used for classification. Previous research on tropical wood species recognition systems considered methods for wood species classification based on linear features. Since wood species are known to exhibit nonlinear features, a Kernel-Genetic Algorithm (Kernel-GA) is proposed in this thesis to perform nonlinear feature selection. This method combines the Kernel Discriminant Analysis (KDA) technique with Genetic Algorithm (GA) to generate nonlinear wood features and also reduce dimension of the wood database. The proposed system achieved classification accuracy of 98.69%, showing marked improvement to the work done previously. Besides, a fuzzy logic-based pre-classifier is also proposed in this thesis to mimic human interpretation on wood pores which have been proven to aid the data acquisition bottleneck and serve as a clustering mechanism for large database simplifying the classification. The fuzzy logic-based pre-classifier managed to reduce the processing time for training and testing by more than 75% and 26% respectively. Finally, the fuzzy pre-classifier is combined with the Kernal-GA algorithm to improve the performance of the tropical wood species recognition system. The experimental results show that the combination of fuzzy pre-classifier and nonlinear feature selection improves the performance of the tropical wood species recognition system in terms of memory space, processing time and classification accuracy.

ABSTRAK

Pengelasan spesies kayu tropika menimbulkan cabaran ekonomi yang besar dan kegagalan untuk mengelaskan spesies kayu dengan tepat boleh memberi kesan yang ketara kepada industri kayu. Oleh itu, sebuah sistem mengenal spesies kayu tropika automatik telah dibangunkan di Pusat Kecerdikan Buatan dan Robotik (CAIRO), Universiti Teknologi Malaysia. Sistem ini membuat pengelasan spesies kayu menggunakan analisis tekstur dimana gambar pelbagai imej permukaan kayu dirakam dan ciri-ciri diekstrak dari imej-imej ini sebelum digunakan untuk pengelasan. Sebelum ini, kajian-kajian pengelasan spesies kayu tropika menggunakan kaedah pengelasan spesies berdasarkan ciri-ciri linear. Memandangkan spesies kayu dikenali untuk mempamerkan ciri-ciri tidak linear, penggunaan Kernel-Algoritma Genetik (Kernel-GA) dicadangkan di dalam tesis ini untuk melaksanakan pemilih ciri tidak linear. Kaedah ini menggabungkan Analisis Diskriminan Kernel (KDA) dengan algoritma genetik untuk menjana ciri-ciri tidak linear dan juga mengurangkan dimensi pangkalan data kayu. Sistem yang dicadangkan mencapai 98.69% ketepatan pengelasan, dengan menunjukkan peningkatan yang ketara berbanding kerja yang dilakukan sebelum ini. Selain itu, pra-pengelas berdasarkan logik kabur juga dicadangkan di dalam tesis ini untuk meniru tafsiran manusia pada liang kayu yang telah terbukti dapat membantu kesesakan perolehan data dan bertindak sebagai mekanisme kelompok bagi pangkalan data yang besar bagi memudahkan pengelasan. Penggunaan pra-pengelas berdasarkan logik kabur mampu mengurangkan masa pemprosesan untuk latihan dan ujian melebihi 75% dan 26% masing-masing. Akhirnya, pra-pengelas berdasarkan logik kabur digabungkan dengan Kernel-GA untuk meningkatkan prestasi sistem mengenal spesies kayu tropika automatik. Keputusan eksperimen menunjukkan bahawa penggabungan pra-pengelas berdasarkan logik kabur dengan pemilih ciri tidak linear berdasarkan Kernel-GA meningkatkan presasi sistem mengenal spesies kayu tropika automatik dari segi ruang memori, masa pemprosesan dan ketepatan pengelasan.

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LIST OF ABBREVIATIONS

APG	-	Angiosperm Phylogeny Group
ASF	-	Adaptive Sequential Floating
BGLAM	-	Basic Grey Level Aura Matrix
BPNN	-	Back Propagation Neural Network
BVO	-	binary vector optimization
CAIRO	-	Centre for Artificial Intelligence and Robotics
CFS	-	Correlation based Feature Selection
c2DPCA	-	column-directional 2DPCA
DFT	-	Discrete Fourier Transform
DLDA	-	Direct Linear Discriminant Analysis
DPSS	-	Diode-Pumped Solid-State
ECG	-	Electrocardiography
EEG	-	Electroencephalogram
EKG	-	Electrocardiogram
exp	-	exponential
FHR	-	Fetal Heart Rate
FN	-	False Negative
FP	-	False Positive
FRIM	-	Forestry Research Institute of Malaysia
FSV	-	Feature Selection Concave
GA	-	Genetic Algorithm

GA-KPLS	-	Genetic Algorithm-Kernel Partial Least Square
GLAM	-	Grey Level Aura Matrix
GLCM	-	Grey Level Co-occurrence Matrices
GNN	-	GA Neural Networks
GSVD	-	Generalized Singular Value Decomposition
IDFT	-	Inverse Discrete Fourier Transform
KDA	-	Kernel Discriminant Analysis
KDDA	-	Kernel Direct Linear Discriminant Analysis
K-GA	-	Kernel-Genetic Algorithm
KNN	-	K-Nearest Neighbours
KPCA	-	Kernel Principle Component Analysis
LDA	-	Linear Discriminant Analysis
LFDA	-	Local Fisher Discriminant Analysis
LI	-	Lumen-Intima
MA	-	Media-Adventitia
maxPores	-	maximum pores
mBm	-	multi-fractional Brownian motion
MF	-	Membership Function
MTIB	-	Malaysian Timber Industry Board
MMG	-	Mechanomyography
mm^2	-	per square millimetres
MRI	-	Magnetic Resonance Imaging
N-East	-	North-East
NN	-	Neural Network
PCA	-	Principle Component Analysis
PF	-	Posterior-Fossa
PLS	-	Partial Least Regression

PPGs	-	Photoplethysmograms
PSO	-	Particle Swarm Optimization
PZMI	-	Pseudo Zernike Moment Invariant
RBF	-	Radial Basis Function
RNN	-	Recurrent Neural Network
S-East	-	South-East
SEM	-	Scanning Electron Microscopy
SFFS	-	Sequential Floating Forward Selection
SPPD	-	Statistical Properties of Pores Distribution
SSS	-	Small Sample Size
SVD	-	Singular Value Decomposition
SVM	-	Support Vector Machines
TP	-	True Positive
VSDP	-	Vision System Development Transform
w-KNN	-	Weighted KNN
1-NN	-	1-Nearest Neighbour
$(2D)^2$PCA	-	two-Directional two-Dimensional PCA

CHAPTER 1

INTRODUCTION

1.1 Introduction

Malaysia is blessed with abundance of wood supply. Statistics from Malaysian Timber Industry Board (MTIB) shows that exports of timber and timber products for the period of January to August 2012 were RM13.18 billion. India, USA and Japan were the major importers for timber and timber products from Malaysia contributing RM 893 million, RM 1.66 billion and RM 2.66 billion worth of export respectively.

The need for automatic wood identification system is becoming critical in the timber industry with the intention to sustain and improve productivity and quality of the timber products in furniture industries and housing industries (Piuri, 2010). The accurate classification of the wood species is very crucial to guarantee that the timber merchandise has the necessary features and characteristics. For instance, the correct wood species must be used for the safety in construction industries. Choosing and ensuring the correct wood to be used is very important to construct a dependable roof truss. In addition, wood with satisfactory strength should be used.

Illegal logging is one of the concerns encountered by timber exporting countries for instance Malaysia. According to a report issued by the United Nations Environment Programme (UNEP) and INTERPOL, it is estimated that prohibited logging accounts for 50-90% and 15-30% of the volume of entire forestry in key producer tropical countries and globally respectively. In the meantime, the economic value of global illegal logging which includes processing is expected to worth between US$30 and US$ 100 billion. Any acts related to logging not with accordance to the national law are considered illegal logging including harvesting, transporting, buying, selling and processing illegally logged timber. These acts are made legal by fraudulent labeling of timber.

There are many negative environmental impacts from illegal logging. Wood species diversity will be reduced because of the widespread illegal logging. Illegal logging also drives climate change. Fewer forests will increase the amounts of greenhouse gases entering the atmosphere which will then contribute to global warming. In addition to the environmental damage, fraudulent labeling practiced by some timber exporters will reduce the country's incomes generated by tax. This is because lower tax will be imposed when high quality wood is labeled as low quality (Ruhong Li, 2008).

One of the ways to prevent illegal logging is by providing a more strict inspection at trading checkpoints. These would require trained wood species inspector to classify the wood species.

1.2 Automatic Tropical Wood Species Recognition System

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. This is because there are more than 3000 tropical wood species and it is impossible to be able to classify each one of them without lengthy, years of training experience. Moreover, the possibilities of biasness and mistakes by human wood graders have to be considered. Besides that, it is impractical and cost ineffective for a human to analyze and identify large number of timber species (Khairuddin *et al.* 2011). Therefore, a reliable automatic wood recognition device is needed in order to classify the wood species efficiently.

This thesis presents a nonlinear feature selection algorithm to solve the nonlinearities in the wood features and the large variations of features within inter and intra wood species. The nonlinear feature selection is a novel approach to the tropical wood species recognition system. The limitations regarding the preservation of class discrimination are shown when classes are originally separated by nonlinear decision boundaries. The implementation of the nonlinear feature selection aims to maintain the most salient nonlinear wood features that minimizes the inter-class distance and maximizes the intra-class distance in order to classify the wood species efficiently. Another objective of implementing nonlinear feature selection algorithm is to find a transformation that maps data to a lower dimensional space where important information is largely preserved.

In this thesis, the strong capability of the Genetic Algorithm (GA) in feature selection is effectively combined with the capability of the Kernel Discriminant Analysis (KDA) which can perform nonlinear dimension reduction without substantially downgrading the system's performance. KDA is a nonlinear extension of linear discriminant analysis (LDA) by using radial basis function (RBF) kernel. The proposed kernel-GA method acts as an enhanced feature selection, to perform nonlinear feature selection.

Besides that, large wood databases presented a problem of large processing time especially for online wood recognition system. In view of this problem, this thesis proposes the use of a fuzzy-based pre-classifier which mimics the human interpretation on wood pores as a means of treating uncertainty to improve the classification accuracy of tropical wood recognition system. The pre-classifier serves as a clustering mechanism for the large database simplifying the classification process making it more efficient. The proposed pre-classifier also aims to reduce the processing time in the training and testing stages of the wood species classification, albeit the existence of the bottleneck in building automatic wood species recognition system.

The linguistic interpretation of the human behavior, provided by a fuzzy model, could be useful to experts in determining the wood species. Moreover, it could improve the man-machine interface in environments for computer-aided training of human operators. The advantage for using fuzzy if-then rules for wood classification problem is that knowledge acquisition can be achieved for users by carefully checking these rules discovered from the training patterns.

1.3 Research Objectives

The objectives of this research are as follows:

a) To analyze the effect of the nonlinearity of the wood features to the classification accuracy of the wood recognition system.
b) To use suitable kernel technique to generate the most discriminative nonlinear features
c) To develop and implement a nonlinear feature selection algorithm using Kernel-Genetic Algorithm (K-GA)
d) To develop a pre-classifier based on fuzzy logic to improve the efficiency of the tropical wood species recognition system
e) To analyze the effectiveness of combination of the proposed nonlinear feature selection with fuzzy logic pre classifier.

1.4 Study Scope and Limitations

a) A tropical wood species database which consists of 52 wood species was built in CAIRO using the wood samples provided by FRIM to perform this project.
b) The feature extractors used are grey level co-occurrence matrices (GLCM), basic grey level aura matrix (BGLAM) and statistical properties of pores distribution (SPPD)
c) This research focuses on solving nonlinear problems in classifying wood species. The nonlinear methods that are studied to solve the nonlinear problems in tropical wood species recognition system are kernel-genetic algorithm (K-GA) as nonlinear feature selection and fuzzy-based pre-classifier.
d) This research focuses on kernel extension of LDA
e) System's efficiency includes : classification accuracy, database size and processing speed.

1.5 Research Contributions

a) Proposed a nonlinear feature selection technique by using kernel-genetic algorithm.
b) Proposed a fuzzy-based pre-classifier to pre-classify the wood species based on pores characteristics which mimics human interpretation on wood texture.
c) Proposed the combination of fuzzy-based pre-classifier and nonlinear feature selection to improve the performance of the tropical wood species recognition system.

1.6 Thesis Outline

The arrangement of this thesis is as follows:

- Chapter 1 - Introduction

  This chapter explains the need of the automatic wood species recognition system and the algorithms proposed to improve the performance of the tropical wood species recognition system. Problem statement, objectives, scope of study and also the research contributions of this doctor of philosophy research were included in this chapter.
- Chapter 2 - Literature Review

  This chapter presents the process of manual wood inspection, the nonlinearity in tropical wood features, and the basic process of an automatic wood species recognition system. This chapter also discussed in detail the work done by other researchers that inspire this research and provide knowledge on various techniques and algorithms that can be used in this research.
- Chapter 3 - Methodology

  This chapter explains the proposed methodologies and processes involved in implementing and improving the automatic tropical wood species recognition system in this research.
- Chapter 4 - Experimental Results and Discussions

  This chapter presents the results of various experiments conducted in this research along with the analysis and discussions.
- Chapter 5 - Conclusions

  This chapter concludes the work done for this doctor of philosophy's research and future works that can be done to improve this research.

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