METHOD FOR SOLVING NONLINEARITY IN RECOGNISING TROPICAL WOOD SPECIES

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A thesis submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy (Electrical Engineering)

Faculty of Electrical Engineering
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To my beloved husband and daughter
ACKNOWLEDGEMENT

Alhamdulillah. Thank you Allah The Almighty for enabling me to successfully complete my doctor of philosophy’s research.

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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 Kernel-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

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<tr>
<td>APG</td>
<td>Angiosperm Phylogeny Group</td>
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<td>ASF</td>
<td>Adaptive Sequential Floating</td>
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<td>BGLAM</td>
<td>Basic Grey Level Aura Matrix</td>
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<td>BPNN</td>
<td>Back Propagation Neural Network</td>
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<td>BVO</td>
<td>binary vector optimization</td>
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<tr>
<td>CAIRO</td>
<td>Centre for Artificial Intelligence and Robotics</td>
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<tr>
<td>CFS</td>
<td>Correlation based Feature Selection</td>
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<td>c2DPCA</td>
<td>column-directional 2DPCA</td>
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<td>DFT</td>
<td>Discrete Fourier Transform</td>
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<td>DLDA</td>
<td>Direct Linear Discriminant Analysis</td>
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<td>DPSS</td>
<td>Diode-Pumped Solid-State</td>
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<td>ECG</td>
<td>Electrocardiography</td>
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<td>EEG</td>
<td>Electroencephalogram</td>
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<td>EKG</td>
<td>Electrocardiogram</td>
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<td>exp</td>
<td>exponential</td>
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<td>FHR</td>
<td>Fetal Heart Rate</td>
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<td>FN</td>
<td>False Negative</td>
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<td>False Positive</td>
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<td>FRIM</td>
<td>Forestry Research Institute of Malaysia</td>
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<td>FSV</td>
<td>Feature Selection Concave</td>
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<td>GA</td>
<td>Genetic Algorithm</td>
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<tr>
<td>GA-KPLS</td>
<td>Genetic Algorithm-Kernel Partial Least Square</td>
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<td>GLAM</td>
<td>Grey Level Aura Matrix</td>
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<td>GLCM</td>
<td>Grey Level Co-occurrence Matrices</td>
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<td>GNN</td>
<td>GA Neural Networks</td>
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<td>GSVD</td>
<td>Generalized Singular Value Decomposition</td>
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<td>IDFT</td>
<td>Inverse Discrete Fourier Transform</td>
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<td>KDA</td>
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<td>Kernel Direct Linear Discriminant Analysis</td>
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<td>maxPores</td>
<td>maximum pores</td>
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<td>mBm</td>
<td>multi-fractional Brownian motion</td>
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<td>MF</td>
<td>Membership Function</td>
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<td>MTIB</td>
<td>Malaysian Timber Industry Board</td>
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<td>MMG</td>
<td>Mechanomyography</td>
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<td>mm²</td>
<td>per square millimetres</td>
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<td>Magnetic Resonance Imaging</td>
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<td>PLS</td>
<td>Partial Least Regression</td>
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<td>Acronym</td>
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<td>PPGs</td>
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<td>PSO</td>
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<td>Pseudo Zernike Moment Invariant</td>
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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.


Cao, W., Zeng, Y., Xia, C.M., Cao, H. (2011). Identifying hand-motion patterns via kernel discriminant analysis based dimension reduction and quadratic...


