

A NEW FEATURE EXTRACTION ALGORITHM FOR
OVERLAPPING LEAVES OF RUBBER TREE

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I declare that this thesis entitled “*A New Feature Extraction Algorithm for Overlapping Leaves of Rubber Tree*” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candite of any other degree.

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ABSTRACT

Rubber is one of the major sources of national income in Malaysia. Malaysian Rubber Board (MRB) is responsible for the monitoring the quality of rubber to maintain a successful rubber clone breeding program. One of the important factors that affect the quality of raw rubber is the clonal origin of the rubber tree. Currently, clone inspectors classify the rubber tree clones manually using leaf features. There are several features such as leaf tip, leaf base to identify the type of clone. An automated clone classification process is needed to facilitate the inspection process. This research focuses on extracting one of the features for identifying clones which are overlapping leaf features. The challenge of overlapping leaf identification is the similarity of the intensity levels. However, it can be classified using shape and angle of leaves. Therefore, a new feature extraction framework is required to extract shape and angle features. In the new framework, key point extraction method is combined with the nearest neighbor algorithm to extract shape feature. While, angle feature is developed using Hough transform. The proposed method able to detect edge, ridge, and blob features and identify angle between petioles of overlapping leaves. This study identified that angle degrees of the overlapping leaves are in the range between 30° and 55° while angle degrees of non-overlapping leaves are in the range between 55° and 90° . In order to validate the result, the identification method has been tested with fifty rubber leaf images that comprise of both overlapping and non-overlapping features images. The results indicated that forty six overlapping and non-overlapping leaf images matched successfully with correct templates. As a conclusion, the proposed features and their extraction method can be used to identify overlapping and non-overlapping rubber tree leaves.

ABSTRAK

Getah merupakan salah satu sumber utama pendapatan di negara Malaysia. Lembaga Getah Malaysia (LGM) bertanggungjawab untuk memantau kualiti getah bagi mengekalkan kejayaan program pembiakan klon getah. Ia merupakan salah satu faktor penting yang memberi kesan kepada kualiti getah mentah dan bergantung kepada jenis klon pokok getah. Pada masa ini, pemeriksa klon untuk mengelaskan klon pokok getah dilakukan secara manual berdasarkan ciri-ciri daun. Terdapat beberapa ciri-ciri daun getah yang digunakan untuk mengenalpasti jenis klon pokok getah seperti hujung daun dan pangkal daun. Oleh itu, proses pengelasan klon secara automatik diperlukan bagi memudahkan proses mengenalpasti klon getah. Kajian ini memberi tumpuan kepada penghasilan salah satu ciri-ciri untuk mengenalpasti klon iaitu pertindihan daun. Cabaran untuk mengenalpasti ciri-ciri daun getah yang bertindih menjadi sukar kerana tahap keamatan diantara daun adalah sama. Walaubagaimanapun, ianya juga boleh diklasifikasikan berbanding bentuk daun dan sudut tangkai yang terdapat pada daun. Oleh itu, satu kaedah pengekstrakan ciri-ciri daun baru diperlukan untuk mengeluarkan bentuk daun dan sudut pada tangkai. Dalam kaedah ini, kaedah pengekstrakan kunci utama digabungkan bersama algoritma kejiranan terdekat digunakan untuk mengekstrak ciri-ciri bentuk daun getah. Manakala untuk mendapatkan ciri-ciri sudut pula, ia dibangunkan dengan menggunakan kaedah Hough Transform. Kaedah yang dicadangkan dapat mengesan kelebihan, rabung, ciri-ciri tompok dan mengenal pasti sudut antara tangkai dan daun yang bertindih. Kajian ini berjaya untuk mengenalpasti darjah bagi sudut daun yang bertindih iaitu dalam julat di antara 30° dan 55° manakala darjah sudut bagi daun yang tidak bertindih ialah dalam julat di antara 55° dan 90° . Bagi mengesahkan keputusan kajian, sebanyak lima puluh imej daun getah telah diuji. Keputusan menunjukkan bahawa empat puluh enam imej daun bertindih dan tidak bertindih berjaya dipadankan dengan betul. Kesimpulannya, ciri-ciri daun getah yang dicadangkan dan kaedah pengekstrakan yang dihasilkan boleh digunakan untuk mengenal pasti daun pokok getah bertindih dan tidak bertindih.

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LIST OF ABBREVIATIONS

| | | |
|------|---|--|
| SIFT | - | Scale Invariant Feature Transform |
| FAST | - | Features from Accelerated Segment Test |
| MRB | - | Malaysia Rubber Board |
| LGM | | Lembaga Getah Malaysia |
| RRIM | - | Rubber Research Institute Malaysia |
| HT | - | Hough Transform |
| ROI | - | Region of Interest |
| GLCM | - | Grey Level Co-Occurrence Matrices |
| IDSC | - | Inner Distance Shape Context |
| CF | - | Contour Flexibility |
| HPM | - | Hierarchical Procrustes Matching |
| DP | - | Dynamic Programming |
| DOG | - | Difference of Gaussian |
| 3D | - | Three Dimensional |
| SC | - | Shape Context |
| TPS | - | Thin Plane Spline |

CHAPTER 1

INTRODUCTION

1.1 Introduction

As Asia's third biggest natural rubber producer and exporter, Malaysia has a vast rubber plantation area (Shigematsu *et al.*, 2011). Maintaining the quality and quantity of the rubber tree is one of the major concerns. Therefore, numerous investigations have been conducted for the sustainability of rubber tree plantations (Ratnasingam *et al.*, 2011; Abdullah *et al.*, 2007). However, image processing based researchers are required to have an extensive amount of rubber leaf images from current clones and primary clones. Therefore, there is a need to establish an image database of rubber clone leaves and classification of them. By establishing a database, the automation of this process for clone classification can be carried out.

Nowadays, plant classification and recognition methods are performed on plant components, such as flowers, leaves, and bark (Khalid *et al.*, 2008). However, reproductive organs, such as flowers, are unfavorable because they are only available for a short period. Thus, leaf based plant classification systems have become more widespread. Typical plant classification methods are proposed based on the unique characteristics of leaves such as shape, color, texture, and margin (Thibaut *et al.*, 2011; Casanova *et al.*, 2009). Existing methods are able to classify different types of plants (Tzionas *et al.*, 2005; Cope *et al.*, 2012). However, they are not suitable for clone classification because the leaves genetically copy similar physical appearances from primary clones. Rubber tree leaves have other sophisticated features that differentiate clones from one another. Leaf tip, leaf base, the form of the leaf, and

leaf margin are among the attributes that might be subject to a different feature extraction method to generate a clone classification method (Benong *et al.*, 2007). Another unique feature is that three compound leaflets radiate from one mutual leaf base (palmate leaflets) (Chan *et al.*, 2005). These leaflets exist in three possible positions: overlapping, touching, or separated. If the position of leaflets is identified using an automation system, this feature can be involved in the clone classification process. However, in current research, overlapping leaf identification is still an open issue because of the foreground leaf and occluded leaf has similar intensity levels. Therefore, this research attempts to develop a framework for identification of leaflet positions by feature extraction of overlapping and non-overlapping rubber tree leaves.

1.2 Problem Background

Current researches on plant classification use a database which is built up from leaf images of different species. Most of the researches employ the features that can identify the plant classes straightforward (Hang *et al.*, 2012; Lee *et al.*, 2013). However, these approaches are not suitable for rubber clone identification because the similarity between rubber clones is significantly high. The reason for that is some of the rubber tree leaves inherited the same genetic features from primary clones. It can be observed that rubber leaves received the similar characteristics.

Meanwhile, the production rate of latex and timber is various depending on clone type. Some clones provide high production while others do not produce as much. Therefore, rubber cultivators are advised by clone inspectors who can differentiate the rubber clones from their leaves. In Malaysia, Malaysian Rubber Board (MRB) has been guiding agricultures for the last 78 years by their professional clone inspectors (Mohd. Nasaruddin and Ahmad, 2007).

MRB has been monitoring the breeding and selection of the rubber clones in order to improve the productivity for more than nine decades (MREC 2010). MRB has categorized the rubber tree clones into two groups; Group 1 consists of high yielding clones based on at least five years yield data. It comprises ten latex timber clones and four latex clones. Group 2 clones are divided into latex-timber clones (2A) and only latex clones (2B). The Group 2A contains all the original clones that are growing well in different ecological conditions (Benong *et al.*, 2007).

The process of clone inspection and verification is very critical because it must guarantee that recommended rubber clones produce the maximum yield in the future. Clones are being examined according to their physical characteristics of leaves in the MRB. However, this clone verification method requires experts with adequate experience. Therefore, this process is initiated into being subject of the current clone classification researches (Abang, 2007).

With an estimated more than 200 Hevea nurseries in the market are inspected and verified by MRB. This is an immense job for limited personnel to handle (Ong *et al.*, 2012). Therefore, the automation of clone recognition is anticipated to make a huge impact on the clone identification in terms of time and efficiency. In addition, this research is the first attempt to extract features of the rubber leaf in the way of clone recognition.

Currently, plant classification and recognition methods are performed on plant leaves (Ehsanirad, 2010). Texture and color based classification methods are unable to recognize rubber tree clones since the leaves are similar to each other. However, rubber tree leaves have other sophisticated features that differentiate clones from one another. One of the unique features is the compound leaflets radiate from one mutual leaf base. These leaflets exist in three possible positions: overlapping, touching, or separated. This research focuses to develop feature extraction method for overlapping and non-overlapping leaves to identify the position of leaflets.

In general, feature extraction is one of the most difficult tasks in image processing. The rest of the following process, such as object recognition and classification all depends on the quality of the feature extraction process (Bala, 2010; Mahmood, 2012). Feature extraction of the overlapping leaf must address several demanding problems. One of the challenges is that overlapping objects might have similar intensity levels. It is demanding to infer the contour of the occluded part. Therefore, in recent studies, there is a noticeable concentration in the contour based retrieval methods (Kumar *et al.*, 2012; Zhang, 2012). Caballero *et al.* (2012) used the contour-based descriptors on their web application for plant species identification. The other plant identification method was done by Bhardwaj *et al.* (2013). Four features are extracted which are area convexity, volume fraction, moment invariant, and inverse difference moment. These features enhance the result of classifying complex images; however it does not consider different leaflet positions.

Although many feature extraction methods have been presented for plant classification, these methods have not considered different clone features to classify within a particular plant (Wu, 2007; Wang *et al.*, 2008). According to studies that have been done on Rubber tree leaves (Md Zain *et al.*, 1997), two features which are shape and angle found out to differentiate overlapping and non-overlapping leaves. However, some are the issues required to be addressed while setting up these new features.

There are many approaches that were proposed by previous researches for overlapping object identification (Valliammal, 2012; Cerutti *et al.*, 2011). The finding from this study discovered that the best method to adopt for this investigation is the key point extraction method (Song and Bin 2013). These methods are able to extract further features such as corner, edge, and blob. Key features of overlapping and non-overlapping leaf can be used to identify similar shapes by comparison of the nearest neighbor algorithm. This process is implemented by building up trained templates consist of various leaves with different positions. Then, key points in the input leaf image are compared with key points of the template image to examine the position of leaflets accordingly (Lowe, 2004). Figure 1.1 demonstrates the example of key point matching from two different images.



Figure 1.1: Finding and Matching Key Points in Two different Images

The problem that needs to be addressed with the key point based feature matching method is to increase the accuracy of the matching result (Liu *et al.*, 2013). Wrong matches can be reduced by setting up larger database. But, the long iteration throughout the matching process is another consideration for key feature based identification. However, in this study, a comparative study is presented for key point extraction to obtain a convincing result in the shape of the leaf positions.

The second feature to identify the leaf positions is angle computation. However, far too little attention has been paid to angle computation between plant petioles. It is clear that previous studies (Stylianidis and Patias, 2000; Weiss, 2008; Chakraborty *et al.*, 2012) has not considered angle features in plant classification methods. Angle between petioles can be detected using line detection methods. Hough transform is an effective tool for the detection of geometric features such as straight lines. However, it requires an attentive line detection in order to deal with the curvy shape of petioles. It is challenging for Hough transformation alone to provide an accurate and efficient straight line to calculate the angle between petioles. Ideally, such a tool like edge detection method would provide precise line detection in order to address accurate angle computation.

1.3 Problem Statement

In general, the clone of the rubber tree can be differentiated through deliberate use of specific features by experts. Current researches have not been considered to develop features of rubber tree leaves yet. However, there are available methods to develop these features. This study addressed the issue of overlapping leaf identification. The research question is:

How to develop a suitable feature extraction method for the positions of the leaves in order to identify the overlapping and non-overlapping leaves?

In order to answer the main issue raised here, the following issues need to be addressed and discussed first:

- i. The features of rubber tree leaves that can be used to identify overlapping and non-overlapping leaves.
- ii. The extraction methods to identify the features overlapping and non-overlapping leaves.
- iii. The development of the identification technique based on the suggested feature extraction method.

1.4 Hypothesis

In this research, there are two features which are shape and angle that can be used to identify overlapping rubber tree leaves. However, there is no definition of shape and angle that currently used for solving overlapping issues. If the features of shape and angle is known, features of overlapping leaves can be extracted and use to identify the rubber clone.

1.5 Aim

This research aims to develop a framework to extract shape and angle features of rubber tree leaf based on their positions and the classification of overlapping and non-overlapping leaves.

1.6 Objectives of the Study

The objectives of this research are:

- i. To identify suitable features of overlapping leaves for rubber tree clone recognition.
- ii. To develop a feature extraction method for overlapping features of rubber tree leaves.
- iii. To develop an identification method for classifying rubber tree leaves that are either overlapping or non-overlapping.

1.7 Scopes of the Study

The scopes of this study are defined as follows:

- i. Data collection has been done at Rubber Research Institute of Malaysia (RRIM), Kuala Lumpur. Data samples are obtained from five different rubber tree clones named RRIM 3001, RRIM 2025, RRIM 2001, RRIM 2002, and PB 350.
- ii. Five trees for each clone and 10 samples from each tree that total of 250 images of rubber tree leaves have been collected.

- iii. The samples of leaves were chosen considering good health condition and undamaged.
- iv. The sample leaves were mature enough which is average two (2) years old.
- v. Samples were collected considering one petiole is included 3 leaves because the rubber tree leaves originate form of 3 leaflets in one petiole.
- vi. The scope of this research is to study the particular features for overlapping rubber tree leaf clone. Therefore, related data regarding to features of rubber tree leaves is obtained from clone inspectors in RRIM, Kuala Lumpur.
- vii. This research focuses on specific features that can be transferred to a computer in order to identify the overlapping leaves. The next stage is the classification of overlapping and non-overlapping rubber tree leaves using MATLAB programming language.
- viii. Noise removal and resampling techniques are applied to enhance the performance of classification results.
- ix. This research considered robustness of the performance on feature extraction and classification.
- x. This research uses rubber tree leaf images that all leaves are in same rotation and direction. Dataset consists of all sample images with leaf tips of middle leaflet are placed to upward direction.

1.8 Significance of the Research

The main significance of this research is that it gives a new concept to explore on enhancement in feature extraction and identification of overlapping and non-overlapping rubber tree leaves in the matter of rubber clone identification. Secondly, this study is sharing a comprehensive list of overlapping leaf features to identify the rubber clone from leaf tip to leaf positions that assists with regard to digital clone recognition system. The findings of this study discovered that there is still restraints

exist in overlapping object identification that more researches must concentrate for further investigation.

One of the more significant findings to emerge from this study is that it demonstrates the result of the most suitable identification method for rubber tree leaflets positions whether they are overlapping or non-overlapping. Issues arise in feature identification and extraction of overlapping object identification has been assessed and a new framework has been introduced for its improvement. The integration of shape and angle feature is proposed to resolve this constraint as a new contribution idea in this study. Template based matching process further supported by the angle feature which provides enhancement toward overlapping leaf identification.

1.9 Thesis Structure

The thesis structure comprises of seven chapters. Chapter 1 is the introduction to the enhancement of feature extraction algorithm to identify overlapping leaves of rubber tree which includes the research objectives, scopes, and significance of the research. The statement of the problem background provides sufficient information in order to make readers clear about the goals of this research.

Chapter 2 covers a thorough review of relevant literature with regard to feature extraction and classification methods. It is initiated with an overview of rubber industry in Malaysia and general features of rubber tree leaves are elaborated in details. In this chapter, plant classification and feature extraction methods are reviewed under two topics which are texture based and shape based methods. With respect to the thesis flow, shape based feature extraction methods are further expanded under key point extraction methods. This chapter also clarifies the geometrical object detection methods for angle feature computation.

Chapter 3 presents the account of the research methods that have been applied in this research and includes a coherent structure that flows logically and smoothly throughout the research. This chapter discusses how the images were sampled and image pre-processing has been carried out. Then, feature extraction, classification and evaluation steps that involved in the methodology were discussed respectively.

Chapter 4 gives extensive descriptions of the feature development stage, feature extraction and evaluation of the feature extraction methods. The result of comparative analysis is discussed under two subsections as key point extraction methods and angle detection methods. SIFT, Harris and Fast methods for shape feature extraction and Hough Transform and boundary tracing methods for angle computation were assessed in this section.

Chapter 5 introduced the enhancement towards robust and accurate rubber tree leaf position identification based on template based and angle based classification framework. It discusses the programming stage, modules, and development of the algorithms.

Chapter 6 presents all of these results of the experiment and the illustrations by the output results and tables. The validation process is conducted initially compared with ground truth dataset, and then comparison of this proposed framework with the result of previous work.

Chapter 7 includes the overall findings and the contribution of the research and conclusions of the thesis. This chapter discusses potential applications of the research findings and limitations of the thesis research. A brief analysis of possible future research directions is also discussed based on this work.

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