UNIVERSITI PUTRA MALAYSIA

DEVELOPMENT OF BASAL STEM ROT DISEASE DETECTION MODEL USING TERRESTRIAL LASER SCANNING DATA OF OIL PALM CROWN STRUCTURE

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By

NUR AZUAN BIN HUSIN

Thesis submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

January 2020

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DEDICATION

This thesis is dedicated to

My lovely family, wife and kids:

With love, respect and a bunch of memories
Indeed, we belong to Allah and indeed to Him we will return.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

DEVELOPMENT OF BASAL STEM ROT DISEASE DETECTION MODEL USING TERRESTRIAL LASER SCANNING DATA OF OIL PALM CROWN STRUCTURE

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January 2020

Chairman : Assoc. Prof. Siti Khairunniza bt Bejo, PhD
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Terrestrial laser scanning (TLS) technology is an active remote sensing imaging method stated to be one of the latest advances and innovations for plant phenotyping and plant structure characterisation. It can provide accurate information via high-resolution scans on tree's dimensions and morphology, which are important indicators of the plant's health and development. Basal Stem Rot (BSR) is the most destructive disease of oil palm in Malaysia caused by white-rot fungus *Ganoderma boninense*. The infected trees show foliar symptoms such as flattening and hanging-down of the canopy, the appearance of many unopened spears, shorter leaves and smaller size of the crown. Various remote sensing approaches have been used to detect BSR. However, none of them using TLS. Furthermore, even the tree dies less than 12 months after infection, current study only monitors the tree at 6 and 12 months after infection. Therefore, this study proposes the use of TLS data of crown properties to detect BSR. This includes the study of crown and frond parts of the oil palm trees to develop a model suitable for BSR detection and also analysis of the changes using multi-temporal data of 2 and 4 months gap. A total of 40 samples of oil palm trees at the age of nine-years-old have been selected with 10 trees for each healthiness level were predetermined by the experts in the same plot. The trees were categorized into four healthiness levels - T0, T1, T2 and T3 represents the healthy, mildly infected, moderately infected and severely infected, respectively. Another 40 samples of oil palm tree taken from different plot were used for prediction. TLS was mounted at a height of 1 m and each palm was scanned at four scan positions at a distance of 1.5 m around the tree. The recorded laser scans were synched and merged to create a cluster of point clouds. Crown stratification was done to get a density of point cloud at specific strata (Cn). Meanwhile, the crown area, frond number and frond angle were gathered by processing the top-view of point cloud data. Analysis of Variance (ANOVA) at 5% significant level and four post-hoc tests - Student's (Student-Newman-Keuls, SNK), Tukey-Kramer HSD (Honest Significance Difference), Hsu's

MCB (Multiple Comparison Best) and Dunnett's were used to find significant features to be used as input parameter(s) of three different approaches of classification models, i.e., single parameter, combined parameters and machine learning. Results of the crown profile have shown that the upper parts of healthy tree are more densed compared to unhealthy. Five features were identified to be significant to classify BSR at four severity levels, namely C200 (strata at 200 cm from the top), C850 (strata at 850 cm from the top), crown area, frond angle and frond number. For a single parameter approach, models developed using frond number and frond angle gave the best results with both gave 100% healthy level classification, 81.67% healthy-unhealthy classification and 72.5% four severity levels of infection classification among all five parameters. Linear model using frond number, frond angle and C200 produced the best result among 118 classification polynomial models with 100% healthy level classification, 86.67% healthy-unhealthy classification and 80% four severity levels of infection classification. For the machine learning approach, the Kernel Naïve Bayes that used PC1 and PC2 as inputs gave the best results with 100% healthy and T1 (mild infection) levels of classifications, 90% healthy-unhealthy classification and 85% four severity level of infection classification compared to other 72 classification models. This model has also been identified as the best model to detect at an early stage and classify the severity level of BSR. Meanwhile, based on the results of multi-temporal analysis, compared to the unhealthy trees, the crown area and frond angle of healthy trees did not give significant changes during 2 and 4 months gap. It shows that even though there were changes in oil palm's architecture due to a normal growth of the healthy trees, the changes were trivial and more stable. It can be concluded that the major contribution of this study is on the development of a model suitable for BSR disease detection in an oil palm tree due to *Ganoderma boninense* and also the capability of the model to classify its severity level of infection at very early stage (T1 – mild infection) using machine learning technique and TLS data of the crown properties. The proposed method hopefully can help better disease management at the oil palm plantation which thus can increase the oil palm yield.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMBANGUNAN MODEL PENGESANAN PENYAKIT REPUT PANGKAL BATANG DENGAN MENGGUNAKAN DATA LASER PENGIMBAS DARATAN DARI STRUKTUR SILARA KELAPA SAWIT

Oleh

NUR AZUAN BIN HUSIN

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Teknologi laser pengimbas daratan (LPD) adalah kaedah pengimejan penginderaan jauh aktif yang dinyatakan sebagai salah satu kemajuan dan inovasi terkini bagi fenotip tumbuhan dan pencirian struktur tumbuhan. Ia dapat memberikan maklumat yang tepat melalui imbasan beresolusi tinggi pada dimensi dan morfologi pokok, yang merupakan petunjuk penting bagi kesihatan dan pertumbuhan pokok. Reput Pangkal Batang (RPB) adalah penyakit yang paling banyak merosakkan pokok kelapa sawit di Malaysia yang disebabkan oleh kulat putih *Ganoderma boninense*. Pokok-pokok yang dijangkiti menunjukkan gejala foliar seperti kanopi yang mendatar dan tergantung ke bawah, penampilan banyak daun pucuk yang tidak terbuka, daun yang lebih pendek dan silara yang lebih kecil. Pelbagai pendekatan penderiaan jauh telah digunakan untuk mengesan RPB. Walau bagaimanapun, tiada satu pun daripadanya menggunakan LPD. Selain itu, walaupun pokok telah mati kurang dari 12 bulan selepas jangkitan, kajian semasa hanya memantau pokok pada 6 dan 12 bulan selepas jangkitan. Oleh itu, kajian ini mencadangkan penggunaan data LPD bagi ciri-ciri silara untuk mengesan RPB. Ini termasuk kajian bahagian silara dan pelepah pokok kelapa sawit untuk membangunkan model yang sesuai untuk pengesanan RPB dan juga analisis perubahan menggunakan data pelbagai tempoh dari jurang 2 dan 4 bulan. Sejumlah 40 sampel pokok kelapa sawit pada usia sembilan tahun telah dipilih dengan 10 pokok untuk setiap tahap kesihatan yang telah ditetapkan oleh pakar dalam plot yang sama. Pokok-pokok tersebut dikategorikan kepada empat tahap kesihatan - T0, T1, T2 dan T3 mewakili masing-masing yang sihat, jangkitan ringan, jangkitan sederhana dan jangkitan parah. Lagi 40 sampel pokok kelapa sawit yang diambil dari plot yang lain digunakan untuk ramalan. Pengimbas LPD dipasang pada ketinggian 1 m dan setiap pohon sawit diimbas pada empat kedudukan imbasan pada jarak 1.5 m di sekeliling pohon. Imbasan laser yang direkodkan telah diselaraskan dan digabungkan untuk menghasilkan kumpulan titik awan (point cloud). Stratifikasi silara telah dilakukan untuk mendapatkan ketumpatan titik awan pada strata tertentu (Cn). Sementara itu, luas silara, bilangan pelepah dan sudut pelepah didapatkan dengan memproses pandangan

atas imej data titik awan. Analisis Varians (ANOVA) pada tahap ketara 5% dan empat ujian pasca-hoc – Student (Newman-Keuls, SNK), Tukey-Kramer HSD (Honest Significance Difference), MCB Hsu (Multiple Comparison Best) dan Dunnett telah digunakan untuk mencari ciri-ciri yang ketara untuk digunakan sebagai input parameter bagi tiga pendekatan klasifikasi model yang berbeza, iaitu parameter tunggal, gabungan parameter dan pembelajaran mesin (machine learning). Keputusan dari profil silara telah menunjukkan bahawa bahagian atas pokok yang sihat lebih padat berbanding dengan tidak sihat. Lima ciri telah dikenalpasti penting untuk mengklasifikasikan RPB pada empat tahap keparahan, iaitu C200 (strata pada 200 sm dari puncak), C850 (strata pada 850 sm dari puncak), luas silara, sudut pelepah dan bilangan pelepah. Bagi pendekatan parameter tunggal, model yang dibangunkan menggunakan bilangan pelepah dan sudut pelepah memberikan keputusan yang terbaik dengan keduanya memberikan 100% klasifikasi tahap sihat, 81.67% klasifikasi sihat-tidak sihat dan 72.5% klasifikasi empat tahap keparahan jangkitan di antara kesemua lima parameter. Model linear menggunakan nombor pelepah, sudut pelepah dan C200 menghasilkan hasil terbaik di antara 118 model pengkelasan polinomial dengan 100% klasifikasi tahap sihat, 86.67% klasifikasi sihat-tidak sihat dan 80% klasifikasi empat tahap keparahan jangkitan. Bagi pendekatan pembelajaran mesin, Naïve Bayes Kernel yang menggunakan PC1 dan PC2 sebagai input memberikan hasil yang terbaik dengan klasifikasi 100% tahap yang sihat dan T1 (jangkitan ringan), 90% klasifikasi sihat-tidak sihat dan 85% klasifikasi empat tahap keparahan berbanding dengan 72 model klasifikasi yang lain. Model ini juga telah dikenal pasti sebagai model terbaik untuk mengesan pada peringkat awal dan mengklasifikasikan tahap keparahan RPB. Sementara itu, berdasarkan analisis pelbagai tempoh, berbanding dengan pokok yang tidak sihat, luas silara dan sudut pelepah pokok yang sihat tidak memberikan perubahan ketara semasa jurang 2 dan 4 bulan. Ia menunjukkan bahawa walaupun ada perubahan dalam struktur kelapa sawit kerana pertumbuhan pokok yang sihat, perubahannya adalah remeh dan lebih stabil. Kesimpulannya, sumbangan utama kajian ini adalah untuk membangunkan model yang sesuai untuk pengesanan penyakit RPB dalam pokok kelapa sawit akibat *Ganoderma boninense* dan keupayaan model tersebut untuk mengkelaskan tahap keparahan jangkitan pada peringkat awal (T1 - jangkitan ringan) menggunakan teknik pembelajaran mesin dan data LPD ciri-ciri silara. Kaedah yang dicadangkan ini diharapkan dapat membantu pengurusan penyakit yang lebih baik di ladang kelapa sawit yang dapat meningkatkan hasil minyak sawit.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Research Background

The oil palm (*Elaeis guineensis*) is a species of palms planted extensively in Southeast Asia and presently is the dominant region of palm oil production. In Malaysia, oil palm is the most important commodity crop and it is the world's second largest palm oil producer. The palm oil industry has been a key economic factor and revenue driver for Malaysia's development and stability. Palm oil and palm-based products are among the top ten major exports for the nation, and its annual export has increased steadily going back more than 30 years (MPOB, 2017). Oil palm products are the second largest export good from Malaysia and production, and export levels continue to increase (Sulaiman et al., 2011). In 2106, exports of palm oil and palm-based agriculture products increased by 5.9% to RM48.27 billion.

Malaysia has a humid tropical climate, ample sunshine coupled with an evenly distributed annual rainfall of around 2000 mm and temperature ranging from 24°C to 32°C throughout the year is highly suitable for oil palm plantation. The land is biophysically highly suitable for oil palm cultivation (Shevade et al., 2019). In 2018, the total area of oil palm planted in Malaysia was more than 5.8 million hectares for mature and immature trees, an increase of almost 100% compared to 1997. These plantations produce 32% of the world's palm oil, which represents 27% of global oil and fat exports (Rakib et al., 2014). Besides the climate and land suitability, government policies (e.g. Industrial Master Plan (IMP)), integrated co-operative from private sector, network cohesion between government and private sector, technology advancement and research and development (R & D) supports are among the key drivers of palm oil sector in Malaysia (Sime Darby, 2009).

White-rot fungus identified as *Ganoderma* is the causal pathogen of BSR disease (Naher et al., 2013). Due to BSR, Malaysia has recorded yearly losses up to RM 1.5 billion (around USD 400 million) (Chong et al., 2017). From the study, it was found that *Ganoderma* attack can lead to yield reduction of fresh fruit bunches (FFB) up to 4.3 tonnes per hectare and was estimated a total of 400 000 hectares could be affected in the year 2020, which sum up to 1.72 million tonnes of FFB yield reduction (Kannan et al. 2017). According to Naher et al. (2013) and Chong et al. (2017), *Ganoderma boninense* species is known as the most devastator species to cause a great economical effect in the palm oil industry especially in Southeast Asia. This disease can cause considerable damage in estates and is one of the main limitations of long term oil palm crop management. BSR could impact the world's supply of palm oil for Malaysia and cause huge economic losses.

Ganoderma produces many enzymes that impair the woody tissue and damage lignin and cellulose of oil palm tree. As the fungus destroys the palm wood internally, it affected xylem (water and solutes transport tissue), thus causing severe problems in the distribution of water, macronutrients and micronutrients to the top of tree (Markom et al., 2009; Mazliham et al., 2008; Su'ud et al., 2007). The lack of nutrients results in the growth of new leaves being affected (Srinivasan, 2001) and in more dead leaves being found. In severe cases, there is no development of new leaves, and no new bunches are found (Srinivasulu et al., 2002). Nutrient requirements generally increase with the growth of plants, and nutrient deficiencies can damage the plants by inhibiting the growth and reducing the yield.

Symptoms of infected oil palm trees are detected visually on the canopy or foliar, stem, or trunk. The foliar symptoms of infected trees are similar to a "skirt-like" shape of the crown, a high presence of unopened spear leaves, and excessive drying of the lower part of the leaves. The leaves also change to pale yellow, have necrotic and chlorotic tips, and become shorter with wilting green fronds (Cooper et al., 2011; Rees et al., 2012). In general, it is hypothesised that healthy trees have larger crown sizes and well-developed canopies compared to infected trees (Barnes et al., 2017; Vossen, 2007; Waring, 1987). BSR infection could cause changes to the physical appearance and growth of oil palm trees. The changes are due to the damage of the internal tissue of trees, which restrict the water and nutrient consumptions, consequently disrupting tree growth and degenerates the physical condition of oil palm trees (Horbach et al., 2011). Infected trees also have less ability to perform normal photosynthesis compared to uninfected trees due to foliar symptoms and water deficiencies (Haniff et al., 2005). The disease at an advanced stage causes more dangled fronds and canopy hanging down than to a skirt structure (Turner and Gillbanks, 1974). Meanwhile, stunted leaf growth also leads to a smaller sized crown (Broschat, 2005; Corley and Tinker, 2008). The impact of the disease on the tree's physical structure is more pronounced and detectable depending on the severity of the infection.

LiDAR (Light detection and ranging) is an active imaging method that emits electromagnetic radiation towards the target using its energy source. LiDAR measures the distance or range to a target with pulsed laser light and measuring the reflected pulses with a sensor. It can directly represent external structures and do profiling for the objects or trees. Research and field site works have used the extensive biometric data in estimating tree properties while offering the possibility of reducing the inventory costs. Previous studies have demonstrated that Terrestrial LiDAR could be used to derive canopy vegetation profiles and other structural tree's properties from an understorey perspective (Detto et al., 2015; Lefsky et al., 2005 and Means et al., 1999). The point cloud resulted from LiDAR can yield information on tree's attributes such as tree height, canopy area, tree basal area, tree stem volume, and fronds properties. The systems can be deployed quickly in several locations and can gather information to measure unique attributes faster than those collected by field workers (Palace, 2016). Balduzzi (2014) stated that research in remote sensing proved that the micro differences visible in the point clouds analysis could be used to detect physical and external changes of the tree on the occurrence of possible disease.

Some of the applications using TLS for rapid, more complete, and more precise tree models were demonstrated by Trochta et al. (2017), Lin and Herold (2016), Palace et al. (2016), Srinivasan et al. (2014), Raumonen et al. (2013), Fernandez-Sarria et al. (2013), Fritz et al. (2013), Kankare et al. (2013), Moorthy et al. (2011) and Kiraly and Brolly (2008). These researchers used the point cloud data from a TLS and extracted the data for parameters such as tree height, diameter based height (DBH), crown height, width and area and plant area index. The results showed that point clouds data from TLS could be used for the extraction of various tree parameters with high correlation.

1.2 Problem Statement

Currently, there is no specific and standard visual symptoms can be used to classify various levels of BSR infection. Lack of a standard coupled with error-prone methods have led to contradictory assessments in the literature (Lelong et al., 2010; Nisfariza et al., 2010). Manual method based on individual or scouts monitoring is labour-intensive, prone to fatigue and low accuracy due to human dependence. Laboratory-based methods are reliable for early detection; however, they are costly, complex, time consuming and ill-suited for outdoor conditions (Naher et al., 2013). Multispectral imaging (Santoso et al., 2019; Bejo et al., 2018; Khairunniza-Bejo et al., 2015; Santoso et al., 2011) and hyperspectral imaging (Ahmadi et al., 2017; Izzuddin et al., 2015; Liaghat et al., 2014; Izzuddin et al., 2013; Shafri et al., 2011a; Lelong et al., 2010; Nisfariza et al., 2010) techniques can differentiate between healthy and unhealthy oil palm trees with varying levels of accuracy. However, these techniques insufficiently discriminate the different levels of severity.

Based on the literature, it can be concluded that TLS is well-adapted for intensive study of tree geometry in-situ. Yet, there exist very few TLS studies focusing on a fine level of oil palm tree architecture, and none is aiming to extract the canopy properties of oil palm tree to study the diseases. The first study on the use of TLS for BSR detection was performed by Khairunniza-Bejo and Vong (2014). The results showed that there were correlations between the oil palm trunk’s perimeter, Diameter-Based Height (DBH) and canopy area with the BSR disease. This preliminary study supported the potential use of TLS for analysing the properties of oil palm trees to distinguish healthy and infected BSR at different levels of infection. Additionally, there is no previous study was conducted to examine the changes in oil palm architectures due to the BSR disease in less than 6 months period, which is the monitoring gap practice in the plantation.

1.3 Objectives

General objective of this thesis is to study the capability of TLS to detect the changes in oil palm crown structure in different stages of *Ganoderma boninense* infection.

The specific objectives of this thesis are:

i. To study the crown and frond parts of healthy and unhealthy oil palm tree infected by BSR disease due to *Ganoderma boninense* using point cloud data.
ii. To develop a model suitable for BSR detection and its severity level of infection at oil palm tree by using single parameters and polynomial models.
iii. To develop a model for early detection of BSR disease using machine learning approach.

1.4 Scope and Limitation

The study area is located at one of the oil palm plantation block at Seberang Perak, Malaysia. A small block was used to avoid variations of the environment. The method was later predicted at another different oil palm plantation block. The age of the trees is 9 years old. The planted tree's breeding is from DxP (*Dura* x *Psifera*) and the soil type is peat, equivalent to soil order of *Histosols* and soil series of *Tropohemist* (soil code: SC-10) (Ramli et al., 2019). Different healthiness level of BSR infection of the oil palm trees was determined by the expert team members from Malaysian Palm Oil Board (MPOB) and was confirmed through lab analysis using GSM (*Ganoderma* Selective Medium) method.

1.5 Structure of the thesis

Chapter 2 presents a review of the growth of oil palm tree, BSR effects and the visual symptoms, and the available methods used for BSR detection. The principles of laser scanning are also described, as well as the review of TLS and LiDAR applications in agriculture, in tree's architecture and canopy. Next, is a review on the temporal monitoring applied in oil palm plantation and other plants. After that is applications of machine learning techniques employed for BSR disease and for various disease in agriculture. The chapter concludes with the advantages of TLS method, literature on temporal data and summary of the literature review chapter.

Chapter 3 presents a proposed method used for BSR detection at the oil palm tree due to *Ganoderma boninense* infection and its severity level classification. First, a brief overview of the study area is given. Then, the standard lab-based method used for *Ganoderma boninense* detection was presented. It was used in this study to confirm the occurrence of *Ganoderma boninense*. It is then followed by a detail explanation on the equipment used in this study – a FARO laser scanner. The experimental setup for data collections was presented later. It involved all consideration taken into account to avoid any occlusion effect and a trial and error setup to get a high density of point cloud which is applicable to be used in this study. After that, a step by step data pre-processing method used is presented. It is then followed by feature extraction for the crown and frond properties. The crown properties section is presenting a method used for crown stratification and crown area calculation. For frond parts, it involves the proposed method to count the frond and method to measure the frond angle. As a reference, manual counting was also presented and used to compare the results of the proposed frond counting. Statistical analysis used in this study was also presented in this chapter. It is then followed by the three types of classification approaches used in this study i.e., single parameters, polynomial model using combined parameters and machine learning techniques. Finally, a method used to study the multi-temporal analysis is also presented in this chapter.

Chapter 4 presents the results and discuss the findings of this research. This chapter first presenting results of the crown and frond analysis in order to find suitable parameters to be used in developing the model suitable for *Ganoderma boninense* detection. This chapter reveals the capability of point cloud data to demonstrate the difference of crown profile for healthy and un-healthy trees due to *Ganoderma boninense* infection. It also presents a list of strata that give a significant difference between healthy and unhealthy trees; and also strata that give significantly different at four severity levels of infections based on the results of statistical analysis. It was then followed by a crown area analysis. After that, this chapter will present how the frond number and frond angle are significant to be used as parameters for BSR detection. The significant parameters at the crown and frond parts were later used as input parameter(s) for classifications. At the classification sections, the results of models developed at all three classification approaches were presented. The best model for each approach was then selected and compared. After that, the analysis about the condition of crown and frond at different healthiness condition of oil palm tree over time are presented. It involved a short duration (2 months gap) and long duration (4 months gap).

Finally, Chapter 5 presents the conclusions of this research. The main contributions of this thesis are clearly outlined. In addition, some suggestions on future work are also presented.

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