Analysis of Changes in Oil Palm Canopy Architecture From Basal Stem Rot Using Terrestrial Laser Scanner

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Abstract

Basal stem rot (BSR), caused by the *Ganoderma* fungus, is an infectious disease that affects oil palm (*Elaeis guineensis*) plantations. BSR leads to a significant economic loss and reductions in yields of up to Malaysian Ringgit (RM) 1.5 billion (US\$400 million) yearly. By 2020, the disease may affect ~1.7 million tonnes of fresh fruit bunches. The plants appear symptomless in the early stages of infection, although most plants die after they are infected. Thus, early, accurate, and nondestructive disease detection is crucial to control the impact of the disease on yields. Terrestrial laser scanning (TLS) is an active remote-sensing, noncontact, cost-effective, precise, and user-friendly method. Through high-resolution scanning of a tree's dimension and morphology, TLS offers an accurate indicator for health and development. This study proposes an efficient image processing technique using point clouds obtained from TLS ground input data. A total of 40 samples (10 samples for each severity level) of oil palm trees were collected from 9-year-old trees using a ground-based laser scanner. Each tree was scanned four times at a distance of 1.5 m. The recorded laser scans were synched and merged to create a cluster of point clouds. An overhead two-dimensional image of the oil palm tree canopy was used to analyze three canopy architectures in terms of the number of pixels inside the crown (crown pixel), the degree of angle between fronds (frond angle), and the number of fronds (frond number). The results show that the crown pixel, frond angle, and frond

number are significantly related and that the BSR severity levels are highly correlated ($R^2 = 0.76$, $P < 0.0001$; $R^2 = 0.96$, $P < 0.0001$; and $R^2 = 0.97$, $P < 0.0001$, respectively). Analysis of variance followed post hoc tests by Student–Newman–Keuls (Newman–Keuls) and Dunnett for frond number presented the best results and showed that all levels were significantly different at a 5% significance level. Therefore, the earliest stage that a *Ganoderma* infection could be detected was mildly infected (T1). For frond angle, all post hoc tests showed consistent results, and all levels were significantly separated except for T0 and T1. By using the crown pixel parameter, healthy trees (T0) were separated from unhealthy trees (moderate infection [T2] and severe infection [T3]), although there was still some overlap with T1. Thus, *Ganoderma* infection could be detected as early as the T2 level by using the crown pixel and the frond angle parameters. It is hard to differentiate between T0 and T1, because during mild infection, the symptoms are highly similar. Meanwhile, T2 and T3 were placed in the same group, because they showed the same trend. This study demonstrates that the TLS is useful for detecting low-level infection as early as T1 (mild severity). TLS proved beneficial in managing oil palm plantation disease.

Keywords: LiDAR, oil palm architecture, *Ganoderma*, crown, frond

Oil palm (*Elaeis guineensis*) is the most edible oil-producing crop that produces an average yield of 4 to 5 tonnes of crude palm oil and 1 tonne of palm kernel oil per hectare yearly (MPOC 2017). The oil palm is the most important agricultural crop in Malaysia. The country is the world's largest exporter of palm oil, with 5 million hectares of plantations producing 32% of the world's palm oil, which represents 27% of global oil and fat exports (Rashid et al. 2014). Oil palm products are the second largest export contributions of Malaysia, and the annual export increases steadily (Sulaiman et al. 2011).

Many diseases can affect oil palm trees, with basal stem rot (BSR) being the deadliest. White rot fungus identified as the genus *Ganoderma* is the pathogen that causes BSR, which leads to significant yield losses (Alam et al. 2015). According to Naher et al. (2013), *Ganoderma boninense* is the main species that affects oil palm plantations in Southeast Asia. However, an early-stage infection is difficult to diagnose (Lubis 1992). As the infection progresses into an advanced stage, the disease will infect the entire tree, and at this stage, it will be too late to prevent the trees from dying. Generally,

symptoms of infected oil palm trees are detected visually on the leaf (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). However, this visual inspection is time consuming, labor intensive (Khairunniza-Bejo and Vong 2014), and sometimes confusing, because it follows an individual observation. Furthermore, no specific standard visual symptoms can classify various levels of infection. Lack of a standard coupled with error-prone method have led to contradictory assessments in the literature (Lelong et al. 2010; Nisfariza et al. 2010).

A rapid, nondestructive, noninvasive, accurate, and real-time detection tool is needed, mainly because oil palm plantations cover a large expansion of land (Khairunniza-Bejo et al. 2015). Laboratory-based methods are reliable for early detection; however, they are costly, complex, time consuming, and ill suited for outdoor conditions. Multispectral imaging and hyperspectral imaging 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. A study shows that light detection and ranging (LiDAR) offers promising results for plant growth and physiology of plant canopy monitoring (Zulkifli and Khairunniza-Bejo 2015). LiDAR scanners obtain geometrical attributes and offers a feasible option for three-dimensional (3D) modeling of tree crops (Colaço et al. 2017).

Terrestrial laser scanning (TLS), known as ground-based LiDAR, is an active, noncontact, precise, cost-effective, and user-friendly

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imaging method. This 3D profiling system provides accurate information about tree dimensions and morphology, which are crucial indicators of plant health and development. Additionally, TLS provides more precise and detailed measurements, reaching up to the millimeter level of accuracy (Wang et al. 2014). The data collected from the scanner are comparably fast and automated. Data acquisition is relatively quick (reaching up to 1 million points per second) for high resolutions (FARO 2016). Moreover, data are unaffected by environmental conditions (except rain), and the scanner is more mobile. TLS penetration to detect diseases in agricultural areas is still limited, especially for the detection of oil palm disease, despite its ubiquity in other applications, such as infrastructure management, urban planning, natural resource monitoring, and forestry. Applications of TLS for precise tree modeling were demonstrated by Fernández-Sarriá et al. (2013), Fritz et al. (2013), Kankare et al. (2013), Király and Brolly (2008), Lin and Herold (2016), Moorthy et al. (2011), Palace et al. (2016), Raunonen et al. (2013), Srinivasan et al. (2014), and Trochta et al. (2017). These researchers used 3D TLS to extract cloud data of two-dimensional (2D) parameters, such as tree height, diameter at breast height, crown height and width, and plant area index. The results showed that the point cloud data from TLS could be used for high-correlation extraction of various tree parameters. Thus, TLS is well adapted for the intensive study of tree geometry in situ. Few TLS studies focus on oil palm tree architecture (Perez 2017); however, none attempt to extract the geometry of oil palm tree structures to investigate a disease. A previous study has proven that the TLS is effective in distinguishing healthy oil palm tree from those infected with BSR (Khairunniza-Bejo and Vong 2014).

The genus *Ganoderma* produces many enzymes that impair woody tissue and damage lignin and cellulose of oil palm trees. The fungus destroys the palm trunks internally, affects xylem (water

and solutes transport tissues), causes severe problems in water distribution, and impairs the macronutrients and micronutrients of the tree (Markom et al. 2009; Mazliham et al. 2008; Su'ud et al. 2007). New leaf growth is affected owing to lack of nutrients (Srinivasan 2001). In severe cases, no new leaves develop, and no new bunches are formed (Srinivasulu et al. 2002). Nutrients increase plant growth, and nutrient deficiencies damage plants, inhibit growth, and reduce yields. Stunted leaf growth also leads to a smaller-sized crown (Broschat 2005; Corley and Tinker 2008). A TLS scanner can be used to differentiate between healthy and unhealthy trees, and it can detect the early stage of the BSR disease.

This study proposes an image processing technique using point clouds taken from the terrestrial laser scanner. The top-down image of oil palm trees measures the crown coverage area, calculates the angle between the tree fronds, and counts the number of fronds on the tree. The differences in oil palm crown and frond properties are used to detect BSR infection and determine the severity level.

Materials and Methods

Terrestrial LiDAR system. The physical characteristics of oil palm trees were measured using the Faro Laser Scanner Focus 3D data (FARO Technologies, Inc.). The FARO laser scanner uses a high-speed laser to acquire millions of 3D laser points for detailed measurement and documentation in a short time. The vertical field of view of each panorama scan is 305°, and the horizontal field of view is 360°. Ground scanning can scan the tree top down by sending infrared laser beams in the center of the rotating mirror before projecting them outward from the scanner to the surroundings. Repetition

Table 2. Classification and tree descriptions (Lelong et al. 2010; Liaghat et al. 2014)

Classification ^a	Trees observations
T0	Healthy tree
T1	Looks healthy but has a presence of fungal fruiting bodies on the stem bark—yellowing or drying of some leaves
T2	Visibility of fungal fruiting bodies and unopened spears; the collapse of lower leaves; some presence of rot at bark stem
T3	“Skirt-like” crown shape; well-developed fungal fruiting bodies, unopened spears, and bole creation

^a T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

Table 1. Technical specifications of FARO LS Focus 3D

Faro Laser Scanner Focus 3D	Hardware specifications
Laser power	Laser class 1
Wavelength	1,550 nm
Range finder/method	Phase shift
Measurement range	0.6–330 m
Ranging error	±2 mm
Field of view (vertical/horizontal)	300°/360°
Data acquisition rate (points per second)	976,000
Maximum vertical scan speed	5,820 rpm or 97 Hz

Fig. 1. Pictures of oil palm trees with varying levels of infection. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

of the single-point measurements is a million times per second; this is the result of a point cloud (a 3D data laser scan of the scanner's environment). The laser scan was recorded on a removable SD memory card, and it was transferred to the SCENE software for preprocessing and postprocessing. SCENE is the specifically designed point cloud manipulation software from FARO used for additional analysis. Table 1 presents the technical specifications of the FARO laser scanner.

Data collection. The study was carried out at an oil palm plantation in Seberang Perak, Malaysia. The trees are 9 years old, with heights between 10 and 11 m (optimum age and height of production). The healthiness of oil palm trees is categorized into four levels: T0 is for trees without the BSR disease, T1 is for mildly infected trees, T2 is for moderately infected trees, and T3 is for severely infected trees (Fig. 1). The categorizations and descriptions shown in Table 2 are given by the Malaysian Palm Oil Board and refer to the findings of Lelong et al. (2010) and Liaghat et al. (2014). In total, there were 40 oil palm trees, with 10 trees randomly selected for each healthiness from different locations in the same plot.

Data collection was carried out in early July 2017. A total of four scanning points were run for each tree. Five to eight reference spheres were placed around the tree, and the scanner was placed at a distance of 1.5 m from the tree depending on obstacles, such as dead fronds and shrubs around the tree. The spheres were used as a reference in case a problem is found when synchronizing the scanned data. Figure 2 shows the data collection setup in the plantation site. A scan with the setting 1/5 resolution and 4× quality took 6.31 min; however, the actual time to complete the scan was around 8 to 9 min. Multiple scanning was tested on the first visit to explore the computer's capability to process data, processing time, and output quality.

Point cloud registration. All collected scans were imported into SCENE for processing and analysis. Then, the scans were registered in the "registration" tab using automatic, manual, and visual methods. Automatic registration was chosen owing to its convenience

and accuracy when using a top-down view cloud-to-cloud method. Confirmation of the clustered scan points was verified based on the recorded scan points and location. Matching between multiple scanning points and synching between laser point data create a cluster of point clouds. After that, the cluster of scan points is viewed in "3D view."

Crown top view. A clipping box was created to view the entire tree sample from different angles—left, right, front, back, and isometric. To standardize the clipping box size for pixel calculation, the length and width were set to 10 m. The clipping box was viewed from the top, and "Save Screenshot" was used to obtain an image of the canopy from above. Paint software was used to crop the images, select the desired part of the image, and remove unwanted features. The images were processed in MATLAB (version 7.5; Mathworks Inc.) software and transformed from RGB to gray. Using Otsu's method, the GRAYTHRESH function in MATLAB computes the image threshold (Otsu 1979). The value minimizes the intraclass variance of black and white pixels. The image was converted to a binary image using the mean and standard deviation. Morphological operations using dilation and erosion based on the STREL function create a flat structuring image and improve image condition. After noise was removed from the image using BWAREAOPEN, the number of pixels in the image was calculated.

Frond section. The frond analysis and crown analysis are similar, and a clipping box was created at the center of the canopy (crown) image. To view the whole tree, the cursor of the clipping box was moved upward to the uppermost part of the tree canopy and to the bottom limit (before the ground). The size of the clipping box was set differently according to the size of the frond area. From the top-down view, the images of the frond were saved and exported to AutoCAD (Autodesk, Inc.). The "Draw" tool was selected; "polyline" drew the line and the shape of the frond. The "Dimension" tool determines the angle between the fronds (measured in degrees). Finally, the angle between the fronds and the number of fronds for each tree were recorded. Figure 3 illustrates the steps of processing the crown top-view image, line drawing the fronds, and dimensioning the angles.

Statistical analysis. The JMP software (SAS Institute) was used for the analysis of variance (ANOVA). The results displayed an overall difference between the levels (omnibus test) but did not show differences at a specific level. Thus, post hoc tests were performed to confirm the differences between levels. Three post hoc tests were used to determine the difference in the group: Student–Newman–Keuls (SNK), Tukey (Tukey–Kramer honest significant difference), and Dunnett. The SNK test computes individual pairwise comparisons. In this test, the farther the two means are on an ordered scale, the more significant the range exceeds the critical value. Tukey test compares the means of every treatment with the means of every other treatment; that is, it applies simultaneously to the set of all pairwise comparisons (Chin 2016). Dunnett test is like a Tukey test, but the comparisons are based on the group and the control. Thus, fewer pairwise comparisons were carried out, because the control would be a healthy level.

Ganoderma selective medium. Using *Ganoderma* selective media (GSM) (Ariffin and Seman 1991), a tissue culture technique verified the *Ganoderma* infection and validated whether the healthy trees were free from disease. Plant tissue culture is a technique to culture a part of a plant aseptically under a specific nutrient and chemical regime. During tissue culture, the growth and development of the tissues are regulated by manipulating the chemicals and nutrient media (Bonga 1982). In GSM, *Ganoderma* fungus grew with the isolation of antibiotics in the media, and fungicides were used to suppress contaminants from other bacteria and fungi (Chong et al. 2011).

Results

Crown pixel. It was hypothesized that oil palm crown areas would be getting smaller, which is concomitant with the level of *Ganoderma* infection. Figure 4 shows that the number of pixels in the crown area (known as a crown pixel) decreases from level T0 to T3. A negative

Fig. 2. Data collection setup. TLS, terrestrial laser scanning.

slope in Equation (1) and a correlation of R^2 equal to 0.79 indicate that the higher the severity level, the smaller its crown spread size.

$$y = -8,126.5x + 96,021 \quad (1)$$

Foliar symptoms, such as dried and yellowed leaves, necrosis, and chlorotic leaves, reduce the chlorophyll pigments during photosynthesis. Plants perform photosynthesis to manufacture food and energy for growth. *Ganoderma* fungus produces numerous enzymes that damage the internal part of the oil palm tree and affect the water-conducting tissues. Such decrease in chlorophyll pigments can provoke water deficiencies, reduce photosynthesis, and lower tree vigor and growth rate. Lack of water also causes nutrient deficiencies, such as of boron, which affects the vegetative and reproductive growth. It also leads to stunted leaf growth and slow development of new leaves. These effects are observed in infected trees owing to their smaller crown sizes (Fig. 5). The ANOVA results show that the crown pixel varies significantly from one level to another (Table 3). A significant factor of a crown pixel was determined by the magnitude of the F values (23.8; $P = 0.05$, $df = 3$).

SNK, Tukey, and Dunnett post hoc tests showed consistent results, where T0 was significantly different from T2 and T3 (Table 4). T0 and T1 overlap; T2 and T3 also overlap. T0 was not significantly

different from T1, because the symptoms were not easily seen in the early stage of infection. T2 was not significantly different from T3, because the symptoms are similar and hard to discriminate. The results show that it is possible to differentiate T0 from T2 and T3; thus, the earliest detection level of *Ganoderma* infection in oil palm trees is at T2.

Fig. 4. Graph of mean crown pixel. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

Fig. 3. Steps of the crown pixel and frond processing.

FronD angle. Figure 6 shows the minimum, mean, and maximum angles between fronds (known as frond angle), where all values are increasing from healthy (T0) to unhealthy (T3). The relationship is shown through positive linear regression by a value of R^2 (0.96). This shows that the degree of angle between fronds increases with the levels of infection.

The graph shows that healthy trees have narrower angles between fronds compared with unhealthy trees. Leaves of oil palm trees are produced in spirals. At the trunk of healthy trees, the normal growth of fronds has a smaller degree of angle if viewed from the top. The degree of angle between fronds is wider in infected trees, because some of the fronds are missing or collapsing. Moreover, plantation workers normally chopped more dead fronds from the unhealthy trees. Increasing numbers of unopened spears in infected trees also increase the angle between the fronds. The effects are clearly shown in Figure 7, where the more severe the infection, the wider the angle between the fronds. The ANOVA of the degree of frond angle is significant between all levels of infection, with a P value of <0.0001 (Table 5).

All post hoc tests showed consistent results, where all levels were significantly separated with a P value of $<5\%$ and where only T1 and T0 were not separated (Table 6). Although the mean of frond angle for T0 was the lowest, the difference between the mean degrees of frond angle for T0 and T1 (3.1°) was not enough for post hoc tests. Similarly, with the crown pixel, the problem of “early detection” reoccurred because of foliar symptoms at an early stage of infection. At the mildly infected level (T1), leaf symptoms, such as collapsing and drying fronds, are fewer compared with moderately (T2) and severely (T3) infected trees. The unexpanded number of spears was also lower in T1, resulting in a smaller degree of frond angle, like T0.

FronD number. ANOVA results for the frond number varied significantly from one level to another (Table 7). A significant factor for frond number was determined by the magnitude of the F values (56.75; $P = 0.05$, $df = 3$). SNK and Dunnett tests showed consistent results, where all levels were significantly different, whereas the Tukey test showed that only T2 and T3 levels were not significantly different (Table 8) at 5% significance level. Tukey test is stricter or very conservative (less likely to find a significant difference) in type 1 error when the number of groups is small (Tredoux and Durrheim 2002). However, when the number in the groups is large, the Tukey test becomes less strict. The reason is that T2 and T3 levels were not significantly separated.

Figure 8 shows that the minimum, mean, and maximum numbers of fronds decrease from healthy (T0) to unhealthy (T3). A negative slope and a correlation of $R^2 = 0.97$ indicate that the higher the severity level, the lower the frond number. The growth of new leaves on healthy palm trees is linear with time (Legros et al. 2009). The mean and maximum numbers of healthy tree fronds were the highest, revealing an average growth of the fronds for T0 level. In infected palm trees, the fungus had effects on the growth of new leaves, causing more unfolded leaves and unopened spears. These explained the

hindered growth of the infected oil palm trees, because the minimum, mean, and maximum numbers of fronds were decreasing from T0 to T3.

Discussion

In this study, we analyze how changes in oil palm canopy architecture relate to BSR incidences. The new method uses an image processing technique based on point cloud images obtained from a

Table 3. Analysis of variance for crown pixel

Source	df	Sum of squares	Mean square	F ratio	Prob > F
Level	3	4,200,552,081	1.4002e+9	23.795	<0.0001 ^a
Error	36	2,118,411,625	58,844,767		
Total	39	6,318,963,706			

^a Significant at the 5% level.

Table 4. Post hoc means comparison for crown pixel (T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected)

Level	Level	P value (Student–Newman–Keuls)	P value (Tukey)	P value (Dunnett)
T1	T2	<0.0001 ^a	<0.0001 ^a	n/a ^b
T1	T3	<0.0001 ^a	<0.0001 ^a	n/a
T0	T2	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T0	T3	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T1	T0	0.8920	0.9991	0.9982
T3	T2	0.9462	0.9999	n/a

^a Significant at the 5% level.

^b n/a = not available.

Fig. 6. Graph showing the minimum, mean, and maximum degrees of angle between fronds. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

Fig. 5. Examples of crown top-view images for each healthiness level. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

terrestrial laser scanner. The point cloud image of the oil palm canopy from the top view was used to analyze three canopy architectures in terms of the number of pixels inside the crown, the degree of angle between the fronds, and the number of fronds. The R^2 values of the crown pixel, frond angle, and frond number in each tree level were 0.76, 0.96, and 0.97, respectively. They showed a significant relationship and high correlation of the BSR severity level. ANOVA of all parameters showed similar results, where all levels of healthiness were significantly separated by a P value of <0.0001 .

Frond number presented the best result using ANOVA followed by SNK and Dunnett post hoc tests, where the earliest detection of *Ganoderma* infection is T1. Frond angle could separate all of the levels using SNK, Tukey, and Dunnett post hoc tests except for T0 and T1. In crown pixel, T0 is separated from T2 and T3 but still overlaps with T1. Thus, both parameters (the frond angle and the crown pixel) are used to detect the genus *Ganoderma* at the T2 level. However, it is hard to classify T0 and T1, because in mild infection, the symptoms are not obvious and look very similar.

Furthermore, it is hard to separate the crown pixel parameter of moderately infected T2 and severely infected T3, because the symptoms at these levels look almost identical. Moreover, T2 and T3 are placed in the same group, because they showed the same trend. The post hoc tests use different critical values for a mean comparison. However, there is no consensus to identify the most appropriate test. From the data obtained from TLS, the results confirm the initial hypothesis that a top-view image of oil palm trees can be used to measure the coverage area of the crown, identify the angle between the fronds, and count the number of fronds on the tree. The contrast between these characteristics helps in determining the health status of oil palm trees.

The performance of a frond number parameter was at the same level using the hyperspectral approach proposed by Lelong et al. (2010), Shafri et al. (2011), and Liaghat et al. (2014), where almost 100% detection level was achieved at four severity levels. Liaghat et al. (2014) obtained a 97% accuracy rate of classifying the *Ganoderma* severity using the k -nearest neighbors algorithm for oil palm leaf samples. Shafri et al. (2011) achieved 100% separability for mild and severe *Ganoderma* infections by segregating 4-month-old samples in the nursery using a maximum likelihood classifier. Lelong et al. (2010) detected *Ganoderma* infection based on the oil palm canopy reflectance with almost 94% accuracy using the partial least

squares discriminant analysis statistical method. The hyperspectral limitations are its contiguous narrow bands and fine wavelengths. Moreover, the method is time consuming. Researchers must sort the data to transmit only the most important spectra or images (Singh and Dowerah 2010). Compression of the original data must not degrade data quality (lossy compression). The hyperspectral method is based on the leaf color or the spectral reflectance, whereas the TLS method is based on the frond structure (frond angle and frond

Table 5. Analysis of variance for the degree of frond angle

Source	df	Sum of squares	Mean square	F ratio	Prob > F
Level	3	3,114.446	1,038.15	41.285	<0.0001 ^a
Error	36	905.258	25.15		
Total	39	4,019.704			

^a Significant at the 5% level.

Table 6. Post hoc means comparison for the degree of frond angle (T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected)

Level	Level	P value (Student–Newman–Keuls)	P value (Tukey)	P value (Dunnett)
T3	T0	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T3	T1	<0.0001 ^a	<0.0001 ^a	n/a ^b
T2	T0	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T2	T1	<0.0001 ^a	0.0002 ^a	n/a
T3	T2	0.0006 ^a	0.0032 ^a	n/a
T1	T0	0.1799	0.5273	0.3917

^a Significant at the 5% level.

^b n/a = not available.

Table 7. Analysis of variance for frond number

Source	df	Sum of squares	Mean square	F ratio	Prob > F
Level	3	1,002.075	334.025	56.748	<0.0001 ^a
Error	36	211.9	5.886		
Total	39	1,213.975			

^a Significant at the 5% level.

Fig. 7. Examples of frond top-view images for every healthiness level. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

number) and crown pixel obtained from the top-view canopy image. TLS is unaffected by sunlight compared with the hyperspectral method, which depends on the variations of the sunlight, skylight illumination, and other environmental noise. This method is advantageous, especially in dense oil palm plantations where light exposure is limited.

TLS uses laser energy to penetrate the canopy gaps and measure the canopy structure (Dong and Chen 2017). Meanwhile, optical imagery cannot see the lower part of the tree's canopy. TLS permits imaging in different perspectives and repeatable views and requires one-time initial cost for the equipment. The advantages of the TLS technique are the speed, high accuracy, simple setup, and high resolution (Jaboyedoff et al. 2012). The terrestrial laser scanner is beneficial, because it is small, portable, and lightweight and has an extended scanning range. Moreover, it is designed for outdoor applications, and it is suitable in an oil palm plantation area. TLS sensors are cheaper and affordable for remote sensing. It is also easy to manipulate by professionals and nonprofessionals (Liang et al. 2016). TLS point clouds can obtain the top-view image, whereas a 360 camera can obtain a view from above if attached to a drone or UAV.

Thus, a 2D image of an oil palm tree can obtain canopy parameters, such as crown pixel, frond angle, and frond number, to successfully detect and differentiate the BSR disease. In a 2D image, the calculation is faster and easier than a 3D image because of the complex oil palm frond structure. The crown pixel and frond features were the new parameters developed using the top-view 2D image of point clouds for BSR disease detection. This was the first approach of using frond features as the parameters to detect the BSR disease, and it did not require the depth and volume dimensions.

In conclusion, the comprehensive laser point data from the terrestrial laser scanner can identify the geometric features of oil palm trees. Of the three parameters, the frond number performed the best, and frond angle performed better than the crown pixel, where only healthy (T0) and mildly infected (T1) overlapped. The top-down

images of oil palm trees extracted from the laser point data are for the analysis of oil palm canopy architectures. The parameters detect the BSR-infected trees and differentiate the infection level of the trees. This novel image processing technique using the physical properties of the canopy structure is essential for early detection, management, and control of the disease. It was also used for in situ application with the support of preprocessing and postprocessing facilities.

TLS provides tree-level information to attain precision farming goals. The oil palm canopy architecture could be used in detecting and classifying the disease. In the future, the laser scanner will offer a faster scanning time and provide more extensive scanning coverage for the entire plantation. A sensing system using innovative algorithms and onsite technologies could provide more accurate data to establish an up-to-date health database of oil palm plantations.

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Table 8. Post hoc means comparison for frond number (T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected)

Level	Level	P value (Student-Newman-Keuls)	P value (Tukey)	P value (Dunnett)
T0	T3	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T0	T2	<0.0001 ^a	<0.0001 ^a	<0.0001 ^a
T1	T3	<0.0001 ^a	<0.0001 ^a	n/a ^b
T1	T2	<0.0001 ^a	0.0002 ^a	n/a
T0	T1	0.0027 ^a	0.0136 ^a	0.0074 ^a
T2	T3	0.0334 ^a	0.1393	n/a

^a Significant at the 5% level.

^b n/a = not available.

Fig. 8. Graph of minimum, mean, and maximum frond numbers. T0, healthy; T1, mildly infected; T2, moderately infected; T3, severely infected.

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