DETECTION OF STRUCTURAL TREE DEFECTS USING THERMAL INFRARED IMAGING

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ABSTRACT: Early detection of adverse tree health condition can minimize the risk of unexpected tree failure and increase the plant survival rate by providing timely remedial measures. Conventional arboriculture practice relies on visual inspection to assess the tree health condition and to identify tree defects. However, the hidden defects, e.g. cavity, are not easy to be detected using this method. Some advanced assessments, for example using resistograph and tomography, are usually conducted, but these invasive instruments would cause irreversible damage to the trees. Thermal infrared technology which is a non-invasive method provides an alternative solution to detect abnormal tree condition especially structural defects by comparing the difference in surface temperature between healthy part and unhealthy part of a tree trunk. Although some researchers introduced similar ideas in their studies, most of them interpreted the thermal images of trees with visual interpretation only and thus there is a research gap of how to extract the abnormal tree parts automatically. This paper proposed a methodology by combining k-means clustering and Sobel gradient filter to identify the area of the tree trunk with potential hidden defects. This method first groups the trunk area with similar surface temperature into clusters and then determines the locations with large variations of temperature. By combining these two factors, potential cavities can be identified based on the temperature differences. This method has been exanimated with trees in four species groups, where each group has at least one tree known to have structural defects and one healthy tree. This paper also investigated the variables affecting the ability to detect tree cavities from thermal images, e.g. acquisition time, humidity, temperature, light intensity, weather condition, the distance between camera and tree, and surface roughness of tree bark. The optimized capturing conditions have been determined, and the thermal images captured in these conditions can clearly identify the internal cavities of the tree trunk. The results from this study have been verified by a certified arborist with on-site checking of target trees.

1. INTRODUCTION

Thermal infrared imaging is the technology to measures the temperature of an object using a thermal infrared camera. The camera can measure the infrared radiation emitted from the target that an object having a higher temperature emits more infrared radiation. This method is considered as a non-invasive technology to measure temperature as no direct contact with the target is required, which can capture the image at a certain distance with the object (Catena and Catena, 2008). Thermal infrared imaging technique has been used in numerous applications, for example, detecting cracks or leaks of building structures, monitoring the heat flow of electrical components to prevent overheating, regulating the temperature of industrial devices during operations, fast screening of body temperature. By analyzing the absolute temperature of the target object or the relative temperature with its surrounding, the abnormal condition can be spotted out and appropriate action can be taken.

Conventionally, the assessment of tree health condition and the detection of structural tree defects, e.g. wood decay, cavities, cracks, wound, deadwood and split, relies on the professional judgment of arborists with on-site visual inspection (Matheny and Clark, 1994). Early detection of these structural problems minimizes tree failure risk by taking timely action. The delay in detecting these defects would cause irremediable consequences to human life and properties because of the high risk of tree failure. To prevent the unexpected accidents caused by tree failure, the arborists usually use more advanced equipment, e.g. resistograph and tomography, for further investigation if unusual tree condition was found from visual inspection (Vidal and Pitarma, 2019). However, these advance methods are often invasive and would cause irreversible damage to the trees. In addition, some of the defects are not always visibly seen, and thus there is a lack of scientific fast-screening method for identifying the potential hidden structural tree defects.

Researchers investigated the feasibility of applying thermal infrared imaging technology to detect abnormal tree conditions. Vidal and Pitarma (2019) reviewed the studies conducted by other literature on this application. Most of the studies focused on pest detection and water stress detection, but very limited number of them focused on the wood decay as well as cavity. Catena, Palla and Catalano (1990) proposed to detect structural tree defects by analyzing the surface temperature of tree trunk and found that the temperature of tree bark surface presented different temperatures of the wood areas with decay that the temperature of decayed areas are usually cooler than the surroundings. Because of the different moisture content of tree trunk with and without cavity, the emissivity are different which result in different temperature measured by thermal camera even they are in same temperature (Catena and Catena, 2008). The variation of temperature pattern is a symptom of unhealthy condition and enabled early detection of tree cavity in a scientific means. Depending on the type and level of decay, trees would have different cooling effects on the surface temperature. Therefore, this technology can help to estimate the extent of the decay by comparing the temperature difference between healthy and unhealthy part.

Burcham et al. (2011) conducted an experiment to correlate the relationship between the size of voids inside a tree trunk with the surface temperature. Three artificial voids in different sizes were created and thermal images were captured together with a control set without void every 30 minutes for 150 minutes. Air temperature, relative humidity and solar irradiance were recorded for each measurement. The results suggested that thermal images captured on the two smaller voids were sensitivity to the voids, but there was no significant effect caused by the largest void. Leong, Burcham and Fong (2012) evaluated the temperature change of healthy part and decay part during heating up and they suggested to derive the percentage of decay from the temperature ratio between normal part and decay part. However, the relationship was species-dependent and thus large-scale sample collection of woods or trees with different levels of decay was required in order to establish a library for the application of model.

The thermal infrared technique required correct visual interpretation of infrared imaging which depends on the professional judgment of the interpreter (Catena et al., 1990). There are some factors causing the misinterpretation, for example, the obstructions, e.g. leaves and moss, covering the tree bark, the roughness of the tree bark, and the absorption of the infrared radiation by water (Catena, 2003). Catena and Catena (2008) reported that the direct solar radiation could be a source of error which masked the underlying wood temperature and it was hard to identify the structural defects of trees from thermal images which were captured under strong sunlight. From the restrictions found by the researches, the thermal images should be captured under serious considerations to prevent misinterpretation. Catena (2003) suggested not to capture the image with direct sunshine and capture at the shade side of the tree if there is direct sunlight to the target tree. Since water would absorb the energy emission from the tree, the images should not be captured in the environment with high humidity and rainy day. Catena (2003) also suggested thermography can be used in both day and nighttime with temperature ranging from 2 °C to 35 °C.

Though some experiments were conducted by the literature, the number of trees tested was very limited. The interpretation of the thermal images was mainly based on the visual analysis and the external environmental factors were not considered scientifically. Therefore, this paper proposed an automatic methodology to identify the area of tree trunk with potential hidden cavity as well as to analyze the environmental factors which affect the discerning ability of using this method.

2. Data Source

In order to understand the relationship between the temperature, tree defects, species and the condition of thermal images captured, fieldwork was conducted in January and February 2019 to acquire thermal images of four groups of target trees based on tree species. The four species were *Crateva unilocularis*, *Delonix regia*, *Artocarpus hypargyreus* and *Cinnamomum camphora*, and each group has one healthy tree and one tree with known structural defects. Figure 1 illustrates the thermal images of the four trees with cavities. Therefore, there are eight trees in total for this study. Experiment was conducted using thermal camera FLIR T650sc with the specifications listed in Table 1. This camera can capture high-resolution thermal images with high thermal sensitivity with small variation of temperature on a tree.

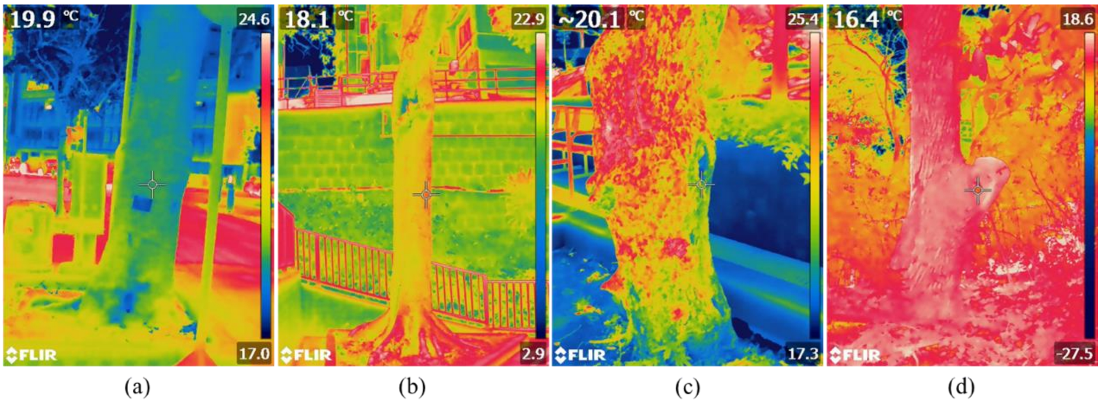


Figure 1. Thermal Images of Tree with Cavity (a) *Crateva Unilocularis*; (b) *Delonix Regia*; (c) *Artocarpus Hypargyreus*; and (d) *Cinnamomum Camphora*

Table 1. Specifications of FLIR T650sc

Item	Specification
Resolution	640 x 480 pixels
Temperature range	-40 °C to 650 °C
Thermal sensitivity	< 0.020 °C
Image frequency	30 Hz
Accuracy	+/- 1 %
Angle of lens	45° x 34°

For each of the target tree, thermal images were captured from the morning to evening (i.e. 9 am to 6 pm). Several stations were set up focusing on a specific area of the target trees, and images were captured at one-hour interval at every station. Figure 2 shows an example of four viewing aspects to a tree *Crateva unilocularis* with known cavity. For each of the measurement, the camera station, time, relative humidity, air temperature, light intensity, weather and the distance between camera and tree were recorded for the analysis of the environmental factors to the thermal imaging processes. Therefore, there are eight to nine thermal images captured at each of the stations and the temporal changes of temperature can be observed. The background of thermal images was then masked out for further processing.

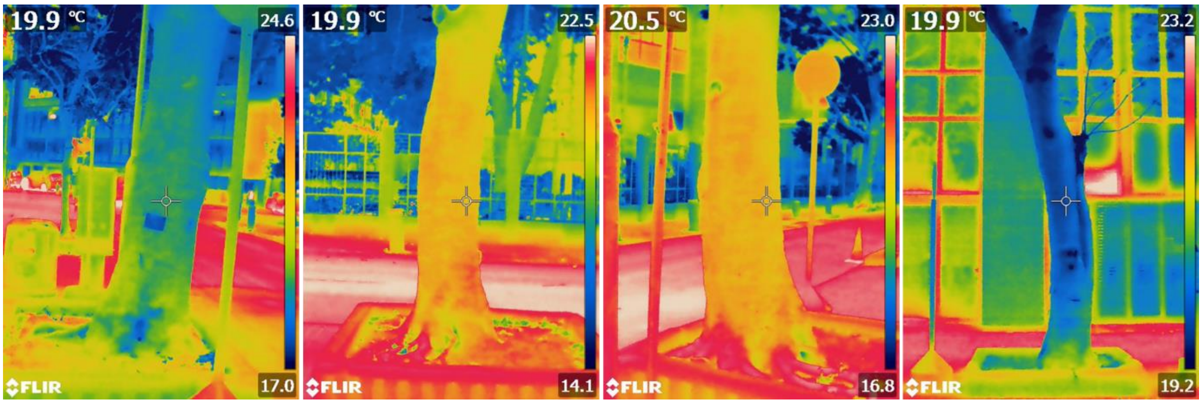


Figure 2. Four Viewing Aspects to a Target Tree *Crateva Unilocularis*

3. METHODOLOGY

3.1 Optimization of Conditions for Data Acquisition

The multi-temporal thermal images captured in the fieldwork were undertaken for analyzing the optimized conditions for data acquisition. Visual analysis was conducted to classify the thermal images into two groups, i.e. good quality and bad quality, in both colour thermal map and the greyscale thermal map. The criterion of the classification depended on whether there existed obvious contrast in temperature between the healthy and unhealthy part of the tree. The images were labelled as bad quality if the temperature distribution was under abnormal condition, for example, the image was unable to show the temperature difference on the tree trunk with existing cavity, large portion of the tree trunk was shaded by the surrounding, unusual temperature distribution existed, the tree was heated by external factors (e.g. a nearby vehicle), etc. Otherwise, the images were labelled as good quality if the known tree cavities were clearly identified.

In order to understand the factors influencing the quality of thermal images for structural defects detection, logistic regression models were developed using the independent variables recorded during the fieldwork, including time, air temperature, relative humidity, light intensity, weather, bark texture, and the distance between camera and tree (Table 2). Among the parameters, time is ordinal; air temperature, light intensity, relative humidity and distance between camera and tree are continuous; weather and bark texture are nominal. Four logistic regression models were generated using (i) colour thermal images only, (ii) greyscale thermal images only, (iii) colour or greyscale thermal images, and (iv) colour and greyscale thermal images.

Table 2. Independent Variables of Logistic Regression

Independent Variable	Type of Variable	Number of Parameters	Range / Parameters
Time (hour)	Ordinal	10	9, 10, 11, 12, 13, 14, 15, 16, 17, 18
Air temperature (°C)	Continuous	-	[16.5, 30.8]
Relative humidity (%)	Continuous	-	[38.0, 92.6]
Light Intensity (lx)	Continuous	-	[0, 6790]
Weather	Nominal	3	Sunny, Sunny with cloud, Cloudy
Tree bark texture	Nominal	2	Smooth, Rough
Distance between camera and tree (m)	Continuous	-	[2, 15]

3.2 Automatic Structural Defect Detection

This paper proposed a methodology to identify the area of tree truck with potential structural defects by combining k-means clustering and Sobel gradient filter. K-means clustering is an unsupervised machine learning algorithm which separates the data into k clusters so that the data are the closest to the centre of cluster (Jain, 2010). Since the literature suggested the cavity usually has a lower temperature when compared with the healthy parts, the clusters with abnormally low temperature can be identified with this approach. The number of clusters (k) and the number of classes with lowest temperature (n) are the critical factors of the clustering result. Different combination results were tested, and Figure 3 shows three of the examples of the clustering results where the temperature increasing from purple, yellow, green and blue. In this study, all the tree trunk analyses were conducted with nine clusters (k = 9) with five lowest temperature classes (n = 5).

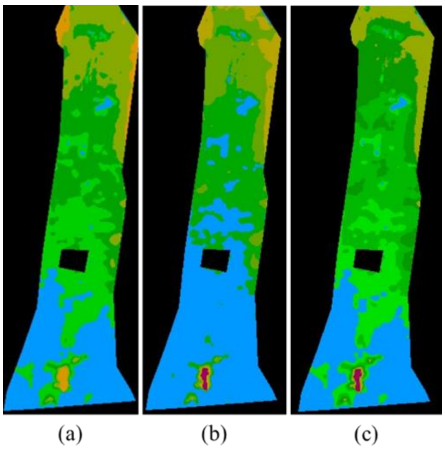


Figure 3. Results of K-means Clustering with (a) k = 8, n = 5; (b) k = 9, n = 5; (c) k = 9, n = 6

Although k-means clustering can identify the clusters with low surface temperature, the cooling effects could be the results of various factors, for example, the shadow cast by the leaves, the wet moss, the change of temperature because of the sunlight. Therefore, the absolute temperature cannot be the only indicator of the symptom of the existence of the cavity. Another element of the potential hidden defect is the sharp change in the temperature caused by the variation of wood density. In order to detect the drastic change of the tree temperature, Sobel gradient filter was used in this study. Sobel gradient filter is an edge detection filter which emphasizes the edges by calculating the approximate derivatives in both horizontal and vertical directions (Gao et al., 2010). Since the variations of temperature change were different in different trees with thermal images captured under environmental conditions, feature scaling was applied to the gradients. With the edges found, a disk maximum pooling was applied to determine the maximum value of gradient within a disk size in a predefined pixel and to estimate the area with large variation of temperature change when compared with the surrounding areas. In this study, disk size of 9 pixels and the threshold value of 0.2 were used to filter out the area which has low level of temperature changes.

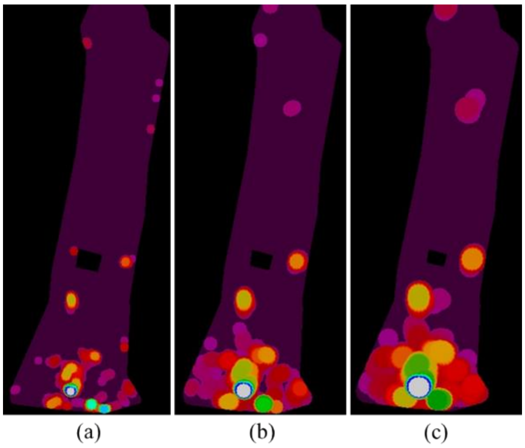


Figure 4. Results of Thermal Images after Applying Sobel Gradient Filter, Feature Scaling and Maximum Pooling (a) Disk Size = 5, Gradient Threshold = 0.1; (b) Disk Size = 9, Gradient Threshold = 0.1; and (c) Disk Size = 13, Gradient Threshold = 0.1

With the combination of k-means clustering and Sobel gradient filter, the areas which have potential hidden structural defects can be identified based on the sharp change of temperature and the relatively low temperature when compared with the other areas.

4. RESULTS

4.1 Optimization of Conditions for Data Acquisition

Table 3 summarizes the results of the significant factors from the four logistic regression models. The results suggested that the capturing time was the critical factor to the quality of image that this factor was found to be significant from all models with p-value smaller than 0.01. From the table, the appropriate image acquisition time ranged from 12:00 to 15:00. The interpretation from visual analysis was also aligned with this finding that the temperature differences between the healthy part of trees and the location with cavity were the highest at noon.

Moderate light intensity, high relative humidity and long distance between camera and tree were also found as significant factors for good image quality, rough tree bark and sunny weather had adverse effects on the images

(Table 3). The factor of moderate light intensity and avoiding the sunny weather agreed with the statement from Catena (2003) that direct sunlight on the tree was not preferred for the purpose of cavity detection. This finding pointed out that the thermal images should be captured at cloudy day and thus the direct sunlight would not cause a considerable impact on the tree surface temperature. The capturing distance and the tree bark texture also decided the quality of the thermal images which increased the level of noise. The very high level of details captured at a close distance or the rough tree bark would affect the generalization ability of the thermal images because of the irregular temperature patterns. Therefore, there is a tradeoff between the spatial resolution which is determined by the capturing distance and the acceptable noise level.

Table 3. Results of Significant Factors from Logistic Regression Models

Image	**P-value**	**Significant Factors**
Colour thermal images	$0.05 \le p < 0.1$	-
	$0.01 \le p < 0.05$	-
	$p < 0.01$	Good quality: • Time: 12:00-14:00
Greyscale thermal images	$0.05 \le p < 0.1$	Bad quality: • Sunny
	$0.01 \le p < 0.05$	Good quality: • Long distance between camera and tree • High relative humidity Bad quality: • Rough tree bark
	$p < 0.01$	Good quality: • Time: 12:00-15:00 • Moderate light intensity
Colour or greyscale thermal images	$0.05 \le p < 0.1$	Good quality: • Long distance between camera and tree • High relative humidity
	$0.01 \le p < 0.05$	Good quality: • Moderate light intensity
	$p < 0.01$	Good quality: • Time: 12:00-14:00
Colour and greyscale thermal images	$0.05 \le p < 0.1$	-
	$0.01 \le p < 0.05$	Good quality: • Moderate light intensity Bad quality: • Rough tree bark
	$p < 0.01$	Good quality: • Time: 13:00-15:00

4.2 Automatic Structural Defect Detection

After determining the suitable conditions for capturing thermal images, the thermal images captured at around noon were extracted and performed the automatic structural defect detection. The true colour images, thermal images, results of k-means clustering, result of Sobel gradient filter and the final detection maps of the four target trees with known defects are shown in Figure 5 to Figure 8, and the control group was presented in Figure 9. In the final detection map, blue area presents a normal condition, while the green, yellow, red and purple represents slight low-level abnormal, low-level abnormal, moderate-level abnormal and high-level abnormal situations.

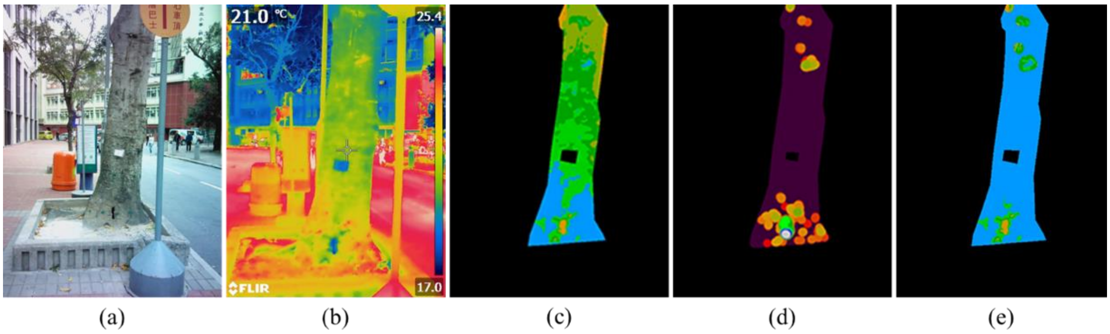


Figure 5. Images of Defect Tree *Crateva Unilocularis* (a) True Colour Image; (b) Thermal Image; (c) K-means Clustering; (d) Sobel Gradient Filter; (e) Final Detection Map

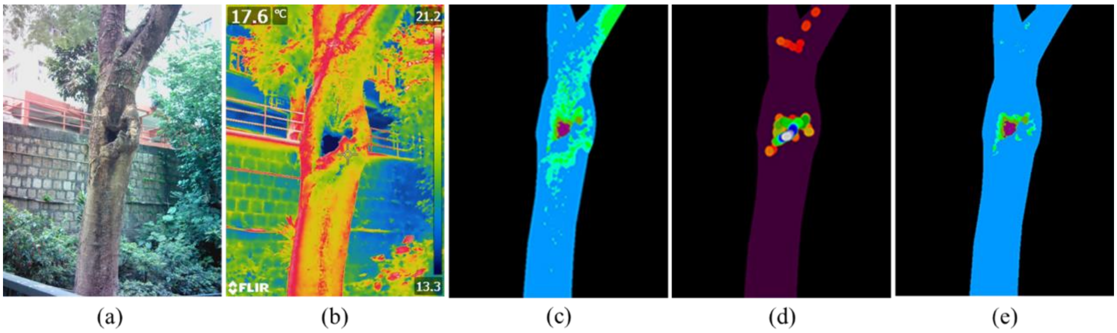


Figure 6. Images of Defect Tree *Delonix Regia* (a) True Colour Image; (b) Thermal Image; (c) K-means Clustering; (d) Sobel Gradient Filter; (e) Final Detection Map

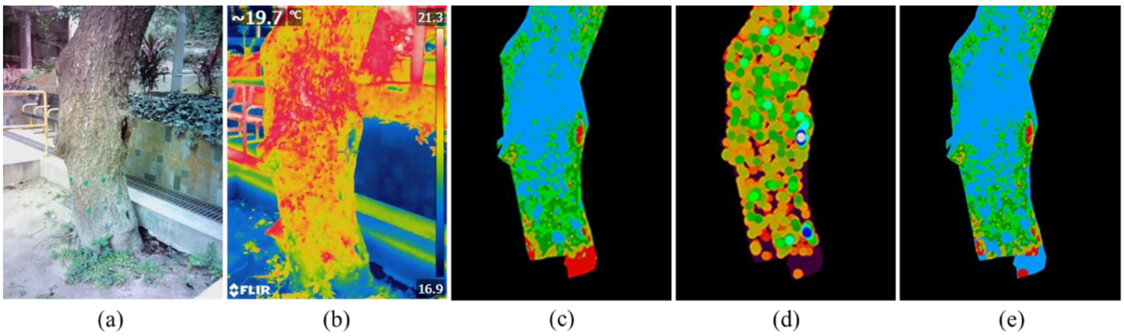
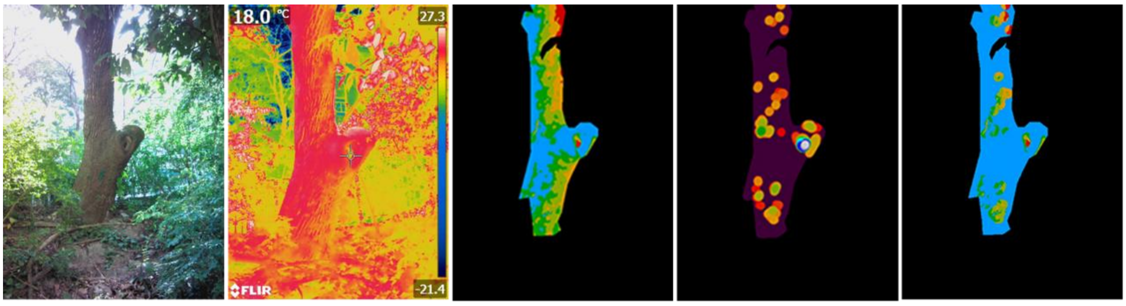
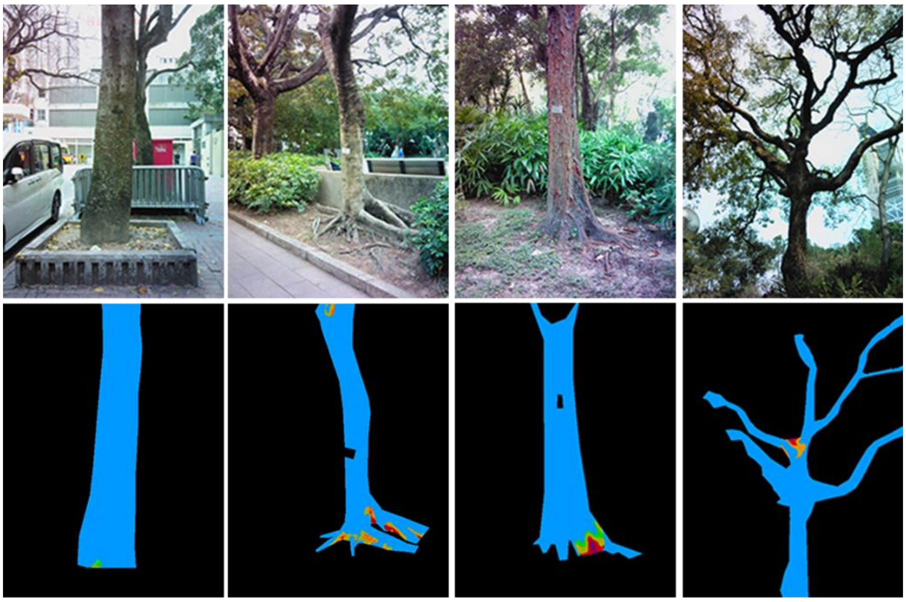


Figure 7. Images of Defect Tree *Artocarpus Hypargyreus* (a) True Colour Image; (b) Thermal Image; (c) K-means Clustering; (d) Sobel Gradient Filter; (e) Final Detection Map



(a) (b) (c) (d) (e)

Figure 8. Images of Defect Tree *Cinnamomum Camphora* (a) True Colour Image; (b) Thermal Image; (c) K-means Clustering; (d) Sobel Gradient Filter; (e) Final Detection Map



(a) (b) (c) (d)

Figure 9. True Colour Image and Final Detection Map of Healthy Trees (a) *Crateva Unilocularis*; (b) *Delonix Regia*; (c) *Artocarpus Hypargyreus*; and (d) *Cinnamomum Camphora*

By analyzing the results of k-means clustering and Sobel gradient filter, the patterns are irregular on trees with rough bark (i.e. *Artocarpus hypargyreus* and *Cinnamomum camphora*). The result suggested that Sobel gradient filter is sensitive to surface bark texture, especially to the species *Artocarpus Hypargyreus*, and the rough bark would cause noise to the result because of the large variation of temperature on the surface. While the Sobel gradient filter maps were smooth with species *Crateva Unilocularis* and *Delonix Regia* which have smooth bark texture, and the maps highlighted the areas with cavities only.

From Figure 5 to Figure 8, the areas with potential structural defects are clearly seen from the detection image. Figure 5 indicated the tree *Crateva unilocularis* has a large cavity at the root plate and two small voids located at the upper part of the trunk. On-site verification was conducted by certified arborist that a cavity exists with dimension of 470 × 140 × 40 mm at tree base. Figure 6 and Figure 8 suggested the tree without internal decay except the voids which are visibly seen, and the on-site checking also agreed with this finding. Figure 7 shows an obvious trend of decay at right hand side of image, although there the noise slight affecting the interpretation. On-site checking found that there were two evident voids at tree trunk, but the internal extent needed further investigation. Therefore, this tree was found suspicious in this study and more in-depth verification will be conducted focusing on this tree by using tomography. By observing the results of healthy trees in Figure 9, the images show large portion of normal condition and confirmed that there were no significant defects or symptom to decay.

5. CONCLUSION AND FUTURE WORK

This paper presents the ability of thermal infrared technology to identify the internal invisible tree cavities with a fast and non-invasive approach with optimized capturing condition and automatic detection method. The proposed method was able to distinguish the trees with and without defect and indicate the extent of internal cavities. The thermal images were recommended to be captured at noon on a cloudy day with longer distance between camera and the tree. Although the rough tree bark is unfavorable to the image quality, this factor is ineradicable. In this study, thermal imaging on the trees with rough tree bark was found challenging in both data acquisition and the algorithm development. To tackle the limitations of this study, more fieldwork will be conducted to capture thermal images with more diverse tree species, more samples for every species and during different seasons. In addition, improvement of the algorithm with rough tree bark will continue with the more samples. Furthermore, field verification will be conducted using professional arboricultural equipment, e.g. tomograph, for comprehensive comparison between the results and tree conditions.

6. ACKNOWLEDGEMENT

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