Research Report for LSGI6813 Guided Study in Remote Sensing

Thermal Infrared Image Analysis for Trees-Health Detection



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Rui Zhu

Department of Land Surveying and Geo-Informatics

The Hong Kong Polytechnic University

Hong Kong, China

Preface

It is my great pleasure to present this research report for trees-health detection using the method of thermal infrared image analysis. Data collecting of this research was mainly supported by Mr. Kwokleung Lee in the Lands Department, the government of the Hong Kong Special Administrative Region. After getting the entrance permission from the government to the restrict region of Hong Kong where many trees were potentially in an unhealthy condition, a data colleting team including the author led by Mr. Lee spent one day to get a sufficient number of thermal images, which would not have been possible without his great leading work. Sincerely thanks also express to the Assistant Professor Man Sing Wong who managed the interactive communication between the Lands Department and the Department of Land Surveying and Geo-Informatics, and conscientiously supervised the research work including the report writing. Finally, heartfelt thanks should send to the MPhil student Siyang Song who volunteered her time for the data collecting work.

Rui Zhu

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1. Introduction

Detecting healthy conditions of trees not only bring benefits for pest control and prevention, forestry protection but also may save people's lives. Extreme news reported that a Hong Kong citizen was killed by a falling-down tree due to its severe decay of the trunk. However, traditional approaches in physical methods to detect the health of trees would easily cause irreversible damages. Nowadays, thermography which could directly record surface temperatures of trees as thermal infrared images is increasingly known as a proved non-invasive method to identify internal damage of trees since certain relationship between cavity / decay of trees and surface temperatures exists (Catena, 2003; Thermography, 2014). However, the specific relationship between the obtained thermal images and the internal decay / damaged tree trunks or the thickness of tree tissues is still uncertainly, which raises a great challenge for the future studies. Current research will take the thermal images for trees in a study area, and design an image processing method to effectively reveal the damaged areas of tree trunks.

2. Related Work

In 1984, Dr. Giorgio Catena and his assistant Lanfranco Palla wondered whether thermal images could be used for detecting internal damages of trees, and they continuously spent ten years of time to ensure there are certain relationship, though has not been identified preciously, between tree decay or cavity and its surface temperatures (Catena & Thermography, 2014). Nowadays, it is well known that damaged area has lower temperatures than that of undamaged area for trees because thermal conductivity of wood decreases with the liquid content decreases which determines the tissue humidity of wood. From then on, many studies focus on the tree or plant health detection based on this theory.

During the past ten years, many studies have being focusing on leafs to detect the plants healthy condition (Costa et al., 2013). One research illustrates that thermographic visualization can be used as an early detection of plant trees, e.g., higher temperature of tobacco leaf infected by tobacco mosaic virus can be detected (Chaerle et al., 2000). Another research measures leaf temperatures for several continuous days and obtains water relations of grapevine canopies by either selecting appropriate areas or identifying a dry-and-wet temperature threshold (Jones, 2002). Although infrared thermography can be used to determine the leaf microclimate through the examined relationship between fungal diseases and the leaf microclimate, it still meets challenges to identify diseased leaf areas (Lenthe et al., 2007). In comparison, fruits locations can be identified in a tree canopy using thermographic technologies (Xu et al., 2004). This study finds that the citrus can be easily segmented in the gray-level image obtained from thermal infrared images because the temperature differences among citrus, branches, and leaves are about one degree centigrade. However, automatically segmenting trunks from their background in thermal images is not easy since temperature variation between trunks and other background objects is not significant enough. To solve this problem, image recognition and even machine learning technologies are needed probably based on the analyzing of visible wavelength images that current thermal infrared cameras also take with the thermal infrared images at the same time instance (FLIR, 2014). While, current study would not use image-recognition based segmentation to extract trunks as a preprocessing considering the truth that segmentation accuracy with the image-recognition method is influenced by many factors (Kaur et al., 2014; Agrawal et al., 2014; Kandwal et al., 2014), and time is not permitted to systematically optimize current segmentation algorithms.

Using the thermograph technique, one study proposes an index of t/R to detect plant health condition within the Visual Tree Assessment (VTA), in which t represents the thickness of tree tissue that keeps healthy and R represents the radius of tree trunk (Mattheck et al., 1994). The closer of this ratio to one, the healthier of the tree is. However, directly measuring t only based on thermal images is impossible but which can be achieved with the assistance of the Resistograph (Catena, 2002). With the similar purpose of detecting internal voids of trees, three quantitative formulas are proposed, i.e., the mean temperature, man relative temperature, and mean normalized temperature, which are used for visualization the external bark defects (Burcham et al., 2011). The continuous study further proposes three indices, namely, the mean variability, the standard deviation, and the distribution symmetry, to determine internal conditions of the trunk based on its thermal images, and this study suggests that the abnormal low surface temperatures are associated with damaged internal parts but this technique cannot clearly determine accurate relationships between the internal condition and its surface temperature distributions (Burcham et al., 2012). It is also noticed that particular relationship between thermal images and the decay stages of trees is still uncertain, which requires further investigation of the mechanism exhaustively to solve this problem (Catena, 2003). Therefore, continuous study for the tree trunk thermal images to reveal the low temperature distribution patterns and to highlight the hidden risk area is hence needed.

Strategies for effectively taking thermal images are also vital to avoid obtaining misleading information in thermal images. It is emphasized that surface of trees should neither been obscured by vegetations and moss nor be in exposure of direct sun shine and raining water when taking thermal infrared images (Catena et al., 2008). This work will be an essential guidance for taking the thermal images in the current research.

3. Research Objectives

Automatically segmenting tree trunks from obtained thermal images would effectively improve the detection efficiency of discovering damaged areas. However, due to the unsatisfied segmentation accuracy of the current image recognition algorithm and the research time limitation as discussed above, current research excludes this research but aims to achieve the following three targets:

- 1. Take a sufficient number of thermal images for tree trunks in a given study area;
- 2. Design a method to effectively reveal damaged areas;
- 3. Discover spatial distribution patterns of the damaged areas for the further studies.

4. Methodology

This part will mainly illustrate four continuous methods to effectively detect internal damaged areas of trunks, i.e., correctly taking thermal infrared images for trunks, effectively highlighting damaged areas, and discovering spatial distribution patterns of the damaged areas.

4.1. Taking Thermal Images

Thermal infrared images were taken by the thermal imaging camera FILR T-Series which has an outstanding thermal sensitivity of distinguishing the temperature difference in less than 0.02 degree centigrade (FLIR T-Series, 2014). Date of the field work was chose on September 25, 2014, and weather condition of which day was satisfied with the requirements for taking thermal infrared images. The distance between the tree and the thermal camera is about 5 to 10 meters as it is shown in Figure 1. The field work took a total number of 172 thermal infrared images and their corresponding of 172 visible wavelength images.



Figure 1. Take thermal infrared images for tree trunks

4.2. Highlighting Potential Damaged Areas

Since segmentation accuracy of the available algorithms is not confidentially high enough and research time is not permitted to significantly improve the automatic segmentation algorithms, e.g., image recognition or machine learning methods, current study would alternatively use manual-based segmentation to extract trunks, and four detailed preprocessing steps are represented below to get the segmented tree trunks.

- **Step 1.** Decompose each thermal image as three independent bands, i.e., red_band, green_band, and blue_band.
- Step 2. Sum the values of the three bands as one integrated band named as sum_band and obtain the maximum value max_v and the minimum value min_v of this band.
- Step 3. Based on the image stretching theory and given the obtained temperature range from the original thermal image, i.e., the highest temperature max_t and the lowest temperature min_t, transform the temperature range of sum_band from [min_v, max_v] to [min_t, max_t] such that the thermal image with RGB value is transformed to the temperature value in degree centigrade as in the Formula 1, where ν represents any given value in the thermal image and t represents the temperature value in degree centigrade that to be obtained.

$$\frac{v - min_v}{max_v - min_v} = \frac{t - min_t}{max_t - min_t} \tag{1}$$

Step 4. Based on the obtained temperature value image in the previous step, interested tree trunks can be clipped by the manual defined polygon / module in the ESRI ArcGIS.

Since range of low temperatures for each individual trunk could vary differently influenced by its own micro-environment and its specific decay / damaged situations, a system-defined low temperature ratio r defined as in the Formula 2 below is given to calculate the temperature threshold t which is used for extract the low temperature areas from the segmented trunks. Notably, max and min in the Formula 2 indicate the maximum and the minimum temperatures respectively in the given segmented trunk image instead of the values in the original thermal image. Based on the system-defined variable rto calculate t could systematically reveal characteristics in spatial distributions and mathematical statistics of low temperature regions varied by r.

$$r = \frac{t - min}{max - min} \tag{2}$$

4.3. Compactness Ratio of the Damaged Area

Many potential damaged areas (i.e. in form of multi-polygons) of the trunk can be obtained based on t that is calculated in the Formula 2 for each given r. Thus, the maximum area of the polygon can be selected from these multi-polygons, which could be viewed as the damaged area in the highest risk. Therefore, defining the shape of this area would be useful to investigate the causes of being damaged and be helpful for the damaged-reason classification. During the past years, many researchers have already tried many methods to define the shape of a random area. An appropriate way is measuring the compactness of an area, which is not related with the size but determined by its shape. In particular, compactness ratio is widely used in many studies (Montero, 2009; Li et al., 2013). This ratio adapts the measurement ranging between 0 and 1. A thin and long shape should have a measurement near to 0; while, an ideal compact shape of the measurement is approaching to 1. Specifically, the formal definition of *compactness ratio* (cr for short) is given in the Formula 3 below.

$$cr = \frac{A}{\pi R^2} \tag{3}$$

In the formula above, A indicates the area of a shape and R represents the radius of the smallest circle that can surround the shape.

4.4. Distribution Patterns of the Potential Damaged Areas

Each obtained potential damaged area is viewed as polygon for the topological calculation. To systematically discover characteristics of distribution patterns for the polygons changing by the variation of r, current research proposes four indices to describe the similarities of size and shape of these polygons (Zhang et al., 2012). TD calculates temperature difference of the segmented trunks, which is a sensitive indicator to measure the healthy condition of trunks. SizeR calculates the ratio of total area of polygons S(t) divided by the area of the segmented trunk S given the temperature threshold t in the segmented trunk as it is shown in the Table 1. ShapeI indicates the complexity of a polygon shape, and P represents the perimeter of the polygon for calculating ShapeI. ShapeS represents the shape similarity for the polygons in two consecutive temperature thresholds. To reveal distribution patterns of polygons, only the maximum areal polygon which is the most representational is considered with the variation of the parameter r.

Table 1. Five indices to reveal characteristics of the potential damaged areas of trunks				
No.	Index	Calculation	Range	
1	Temperature difference of the trunk	$TD = max_t - min_t $	$TD \ge 0$	
2	Size ratio of the polygons	$SizeR = \sum S(t) / S$	$0 \le \text{SizeR} \le 1$	
3	Shape index to measure complexity of the shape	Shape I = $\frac{P}{2\sqrt{\pi S(t)}}$	ShapeI > 0	
4	Shape similarity of the two polygons in two temperature thresholds	ShapeS = $\frac{\text{ShapeI (t2)}}{\text{ShapeI (t1)}}$	ShapeS > 0	

5. Study Area

Hong Kong, located in the subtropical zone of Chinese south coast with high temperatures throughout the year, contains approximately 40% areas of country parks and nature reserves with the 1104 km² territory, which lead the importance of the forestry protection work (Geography of Hong Kong, 2014). Healthy conditions of trees in the urban area of Hong Kong are monitored regularly, which may be difficult to find enough trees having healthy problems. However, a great number of trees in the rural areas are potentially internal damaged. Thus, the study area is chosen in the north region of Hong Kong as it is shown in the red box of Figure 2, in which area trees are seldom protected by humans. A detailed plan about the pedestrian routing for taking thermal infrared images of trees is made before the physical field work. Particularly, these trees, having their own ID numbers, have already been recorded in the government forestry database.

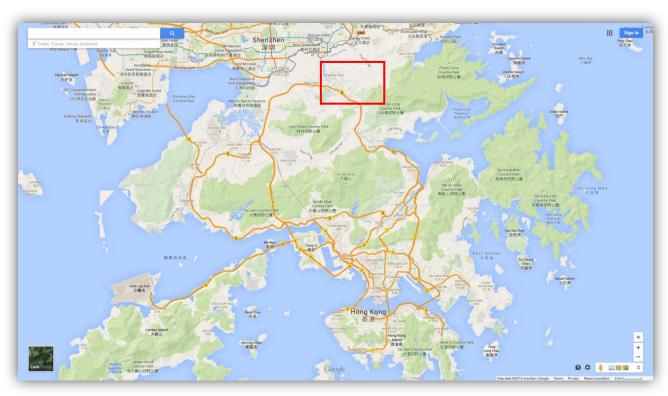


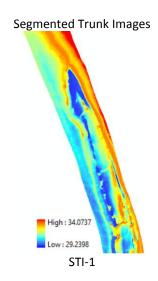
Figure 2. The study area is in the north region of Hong Kong

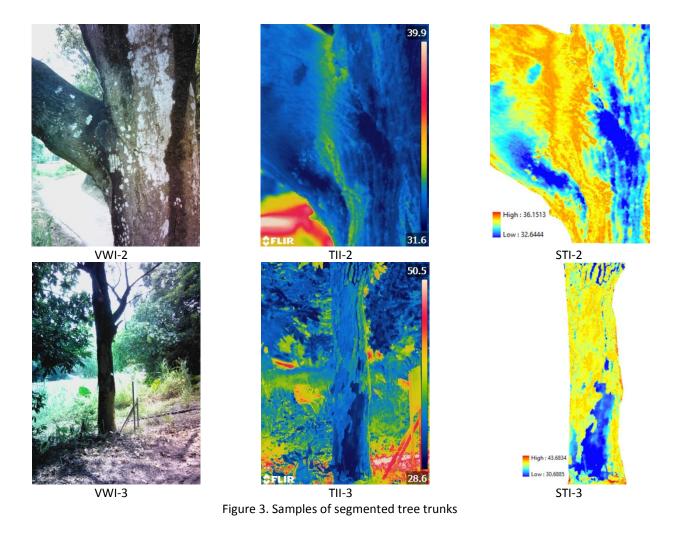
6. Result Analysis

Figure 3 shows three trunk segmentation results, each line of which respectively represents the visible wavelength image (VWI), the thermal infrared image (TII), and the segmented trunk image (STI).









LTA-3 LTA-1 LTA-2 0.1 0.2 0.3

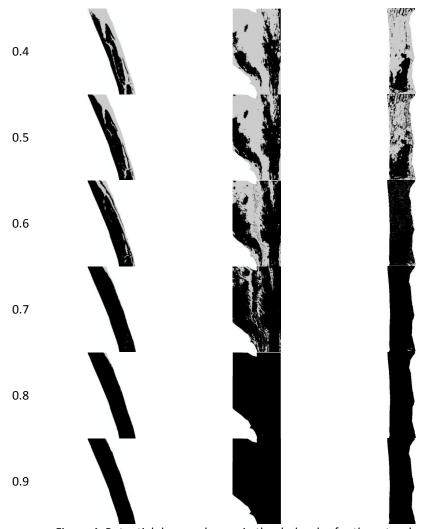


Figure 4. Potential damaged areas in the dark color for three trunks

Figure 4 shows the potential damaged areas, i.e., low temperature areas (LTA), in the dark color of the previously segmented tree trunks. The temperature threshold t is getting higher by increasing the ratio r for 0.1 in each step. The figure also presents that area of the dark-color polygons in each column are increasing with that of r.

Figure 5 describes that SizeR (i.e. vertical coordinate) of low temperature areas in three segmented trunks, i.e., black-color polygons in the Figure 4, is changing with r values (i.e. horizontal axis), i.e., SizeR-1, Sizer-2, and SizeR-3 respectively show size changing ratio of LTA-1, LTA-2, and LTA-3. Growth of SizeR-1 is almost steadily with the biggest slope between 0.3 and 0.4; while, SizeR-2 has a significant growth between 0.6 and 0.7, and SizeR-3 presents a dramatic jumping between 0.5 and 0.6. Essentially, LTAs drawing in the Figure 4 have the highest possibility of being damaged or decayed when r value of each curve reaches the biggest slope in the Figure 5 for the reason that it indicates hug area difference of polygons between two consecutive temperature stamps. By contrast, the lower and the steadier this slope value is, the healthier this trunk could be.

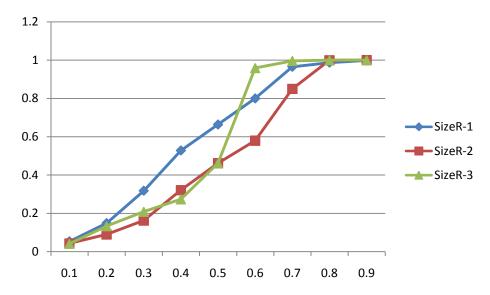


Figure 5. SizeR of the three low temperature areas of segmented trunks

Since when the r value is equal to 0.3, 0.6, and 0.5 for LTA-1, LTA-2, and LTA-3 respectively has the highest possibility to reveal the damaged areas, calculation of the $compactness\ ratio$ for three trunks are only based on this three specific situations. Figure 6 represents the maximum size of the polygon for each trunk when cr values are 0.0703, 0.2333, and 0.1623 for LTA-1 when r is 0.3, LTA-2 when r is 0.6 and LTA-3 when r is 0.5 accordingly. It is obvious that middle polygon for LTA-2 indeed has the highest compact shape, which obtains the highest cr value. By contrast, the left polygon is the thinnest and has the lowest cr value. This compactness ratio is a very sensitive index for measuring the shape of extracted polygon, which is an easy usage for the wild field examine.

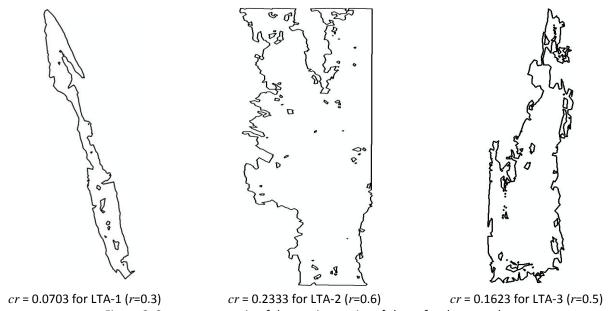


Figure 6. Compactness ratio of the maximum size of shape for three trunks

Table 2 shows the temperature difference (TD) of the three tree trunks. It is obvious that the TD value of STI-3 is significantly higher than the rest two figures, which indicates that this trunk could be severely damaged / decayed or it still possibly due to the manual-based segmentation error, which includes other high-temperature objects. Therefore, this indicator could be useful in both revealing the healthy condition of trunks and examining the segmentation accuracy.

Table 2. DT of the three segmented tree trunks

Name of the trunks	STI-1	STI-2	STI-3
TD	4.8339	3.5069	12.9949

ShapeS measures shape similarity of the two overlapping polygons in two temperature thresholds, which would easily cause confusing or difficulties in statistics for whole of the polygons in one segmented trunk when two small polygons in t1 are merged together as one big polygon in t2 (t2 > t1). This means this indicator is suitable for examining the similarity of each pair of polygons individually instead of viewing it as a global variable. Therefore, an alternative approach in the current research only investigates the changing tendency of ShapeI which can be used to measure complexity of the shape for the polygon which has the maximum area in each temperature threshold. Area of this polygon is likely to grow all the time with the increasing of the temperature thresholds. Based on this idea, Figure 7 shows three curves of the ShapeI for the above mentioned three areal-growing polygons, i.e., ShapeI-1, ShapeI-2, and ShapeI-3 respectively represent for STI-1, STI-2, and STI-3. Specifically, the horizontal axis is for r values and the vertical axis is for ShapeI values. Values of all the curves start around 3, grow differently to the peak values at 4.6 for STI-1, 8.6 for STI-2, and 6.2 for STI-3 respectively, and decrease significantly to the minimum values less than 1.7. The growth of each curve actually reveals the degree of fragmentation or the complexity of the low temperature areas is accordingly growing. However, the considerable decreasing indicates that almost all the polygons are merged together as one which has a relevant simple shape complexity.

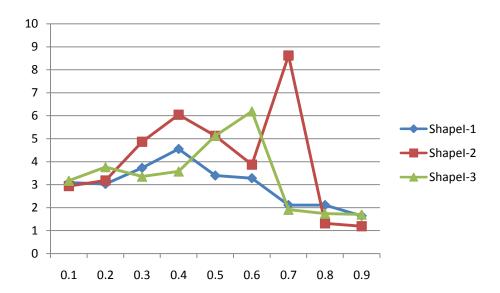


Figure 7. ShapeI of the three low temperature areas of segmented trunks

7. Discussion and Conclusion

Thermal infrared image analysis has been proved to be an effective method to detect healthy conditions for trees. The research firstly collects thermal infrared images of trees in wild fields, uses manual-based segmentation method to extract tree trunks, and finally investigate the characteristics in size, shape and values of tree trunks by the image processing method given a series of temperature thresholds specified by altering the size ratio r. The research has discovered some interesting characteristics in view of shape compact with cr, size changing with SizeR, and shape complexity with *ShapeI* of three tree trunks in the empirical experiment.

Compactness ratio cr could be utilized as a very sensitive index to find out the maximum size of the damaged areas in the highest risks. SizeR could be used as an effective indictor to discover potential damaged / low temperature areas or locations when slope value of the curve is maximized. However, independently using the thermal infrared image is not adequate enough to confidentially determine the damaged areas because it only directly reveals facial temperatures of trunks. ShapeI can be used as an indicator to classify the shape complexity and reveal distribution patterns of low temperature polygons. For example, a low ShapeI value may indicate one polygon, i.e., a tree-hole with a smooth boundary; while, a high ShapeI value may represent a great number of small polygons, i.e., severe diseased insect spots with sawtooth boundaries. TD value for STI-3 is significantly higher than other two values in the Table 2, which is possibly due to the environmental difference but it also may because of the manual-based segmentation error that irrelevant objects in extremely high temperatures are included, which would cause the empirical experimental results to be entirely incorrect and even misleading. Therefore, segmentation accuracy is urgently to be improved.

Based on the discussion above, future research can be proposed in the following three aspects. Firstly, systematically plotting the cr values for the maximum size of polygon given a full range of r values would be possible to find interesting patterns of the potential damaged areas. for Secondly, to effectively determine damaged internal areas of trunks, acoustic wave theories or other technologies may be used to map the internal structures and densities of trunks in different depths such that functional relationships between the facial temperatures and internal structures in any given trunk depth can be specified. Another approach could be physically cut some tree trunks that have been defined as damaged areas for the validation analysis. Thirdly, further investigation could systematically build categories in the relationship between ShapeI / ShapeS and damaged types of different tree species. Fourthly, image recognition and / or machine learning method may be used to process objects classification in the visible wavelength images and use the obtained objects as a model to cut the thermal infrared images to gain high-accurate tree trunk segmentation. Nevertheless, automatic segmentation is also in the great challenge for the reasons that (1) available algorithms cannot achieve the required segmentation accuracy for the present research; (2) complex or similar textural backgrounds in the woods or wild fields may cause the methods even more difficulty in getting a confidentially segmentation accuracy; and (3) processing a series of thermal images can be extremely time consuming.

Reference

- Agrawal, S., Xaxa, D. K., (2014). Survey on Image Segmentation Techniques and Color Models. International Journal of Computer Science and Information Technologies, Vol. 5, No. 3, pp. 3025-3030.
- Burcham, D. C., Ghosh, S., Choon, L. E., King, F. Y., (2011). Evaluation of an Infrared Camera Technique for Detecting Mechanically Induced Internal Voids in Syzygiumgrande. Arboriculture & Urban Forestry, Vol. 37, No. 3, pp. 93-98.
- Burcham, D. C., Leong, E. C., Fong, Y. K., Tan, P.Y., (2012). An Evaluation of Internal Defects and Their Effect on Trunk Surface Temperature in Casuarina equisetifolia L. (Casuarinaceae). Arboriculture & Urban Forestry, Vol. 38, No. 6, pp. 277-286.
- Chaerle, L., Straeten, D. V. D., (2000). Imaging techniques and the early detection of plant stress. Trends in plant science, Vol. 5, No. 11, pp. 495-501.
- Catena, A., (2002). Thermal infrared detection of cavities in trees: an update. Atti Della Fondazione Giorgio *Ronchi Anno LVII N.5*, pp. 761-775.
- Catena, A., (2003). Thermography reveals hidden tree decay. Arboricultural Journal, Vol. 27, pp. 27-42.
- Catena, A., Catena, G., (2008). Overview of thermal imaging for tree assessment. Arboricultural Journal, Vol. 30, pp. 259-270.
- Costa, J. M., Grant, O. M., Chaves, M. M., (2013). Thermography to explore plant-environment interactions. Journal of Experimental Botany, Vol. 64, No. 13, pp. 3937-3949.
- Catena & Thermography. [Online] Available at: http://www.treethermography.it/index.html[Last Accessed: December 4, 2014]
- FLIR. [Online] Available at: http://www.flir.com/cs/apac/en/view/?id=52123 [Last Accessed: December 4, 2014]
- Geography of Hong Kong. [Online] Available at: http://en.wikipedia.org/wiki/Hong Kong [Last Accessed: December 13, 2014]
- Jones, H. G., Stoll, M., Santos, T., et al. (2002). Use of infrared thermography for monitoring stomatal closure in the field: application to grapevine. *Journal of Experimental Botany*, Vol. 53, No. 378, pp. 2249-2260.
- Kaur, M., Singh, E. N., (2014). Image Segmentation Techniques: An Overview. Journal of Computer Engineering, Vol. 16, No. 4, Ver. III (Jul – Aug. 2014), pp. 50-58.
- Kandwal, R., Kumar, A., Bhargava, S., (2014). Review: Existing Image Segmentation Techniques. International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 4, No.4, pp. 153-156.
- Lenthe, J. H., Oerke, E. C., Dehne, H. W., (2007). Digital infrared thermography for monitoring canopy health of wheat. Precision Agriculture, 8 (1–2), pp. 15-26.
- Li, M., Goodchild, M. F., Churchbm R., 2013. An efficient measure of compactness for two-dimensional shapes and its application in regionalization problems. International Journal of Geographical Information Science, Vol. 27, No. 6, pp. 1227-1250.
- Mattheck, C., Breloer, H., (1994). Field guide for visual tree assessment (VTA), Arboricultural Journal, Vol. 18, pp. 1-23.
- Montero, R. S., 2009. State of the Art of Compactness and Circularity Measures. International Mathematical Forum, Vol. 4, No. 27, pp. 1305 - 1335.
- Thermography. [Online] Available at: http://en.wikipedia.org/wiki/Thermography [Last Accessed: October 31, 2014]
- FLIR T-Series. [Online] Available at: http://www.flir.com.hk/instruments/display/?id=62960[Last Accessed: November 8, 2014]
- Xu, H., Ying, Y.B., (2004). Detection citrus in a tree canopy using infrared thermal imaging. *Monitoring Food Safety, Agriculture, and Plant Health,* Vol. 5271, pp. 321-327.
- Zhang, X., Zhao, X., Molenaar, M., Stoter, J., et al. (2012). Pattern classification approaches to machining building polygons at multiple scales. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial *Information Sciences*, Vol. I, No. 2, pp. 19-24.