Saif Uddin et al., Int. J. Sus. Dev. Plann. Vol. 4, No. 2 (2009) 103–111

MAPPING OF PALM TREES IN URBAN AND AGRICULTURE AREAS OF KUWAIT USING SATELLITE DATA

SAIF UDDIN, A. AL-DOUSARI & A. AL-GHADBAN
Environment Sciences Department, Kuwait Institute for Scientific Research, Kuwait.

ABSTRACT
Quickbird panfused data with 60 cm resolution is used to map the locations of date palm trees in the arid land of Kuwait. In this study, Laplacian maxima filtering was applied to classify date palm trees using high-resolution satellite imagery. The processing was done in two steps: the first step involved smoothing of the data using non-linear diffusion and the second was extracting local spatial maxima of Laplacian blob used for palm tree identification. The results are promising and the classification accuracy in the two test areas is 96% and 98%, which is higher than maximum likelihood classification for the same dataset. The results show that this methodology can be adopted for the mapping of palm trees in arid Middle Eastern countries.
Keywords: arid land, blob, image classification, laplacian filtering, quickbird.

1 INTRODUCTION

Palm trees are very common in Middle Eastern countries. They are of significant environmental and commercial importance [1]. In recent decades, the Middle Eastern region has witnessed an extensive planting of Date Palm trees, both in urban and agricultural areas. Millions of trees are estimated to have been planted in these arid deserts [2, 3]. Extensive plantation in urban areas rarely gives a clue that these are arid and hyper arid countries. Among these species, most common are date palm trees, which are seen planted along the roads, in front of houses, in parks, and organized plantation in agricultural areas. However, there is limited knowledge of actual tree counts and their exact spatial locations, which is a requirement for any agricultural census.

Remote sensing data have been used for the identification of urban treed areas, but with limited classification accuracies. These lower classification accuracies are attributed to a variety of spectral and textural properties [4]. Medium resolution satellites including LANDSAT, SPOT, and ASTER have been used in urban treed classification, but their spatial resolution permits only larger patches of treed areas to be classified [4–6]. With the advancement in satellite technology and availability of high spatial resolution images, it is now feasible to achieve higher classification accuracies in urban and agricultural areas. The present study is an attempt to map the date palm trees in urban and agricultural areas of Kuwait. An accuracy assessment is also made to compare results from maximum likelihood and the Laplacian blob classifications of date palm trees within the test areas.

Similar studies for classifying and quantifying olive trees were taken up by European Union Countries. The European Economic Committee realized the need to quantify the olive plantation in 1997 and launched the OLISTAT project in September 1997 to estimate the number of olive trees in France, Italy, Spain, Portugal, and Greece [7]. The counting of trees is a classic example of remote sensing applications in forestry. However, crown counting of trees is not an easy or straightforward task as there are limitations of satellite data resolution as well as problems related to the subjective nature of interpretation. Howard [8] indicated that the capacity to distinguish different objects is governed by the size of the object relative to pixel.

The multispectral classification methods have provided reasonably good results, but there is still room for further improvement in classification accuracy if textural parameters are taken into account. It was believed that with the availability of higher resolution satellite data, classification accuracies

ISSN: 1743-7601 (paper format), ISSN: 1743-761X (online), http://journals.witpress.com
DOI: 10.2495/SDP-V4-N2-103-111

will improve, but ~100% accuracies are yet to be seen. Since the higher spectral resolutions increased the intraclass separability in an image, Marceau [9] suggested that optimal spatial resolution for the classification of temperate forest should be 10m as resolutions finer than 10m increased the intraclass separability and decreased the overall classification accuracy.

The inclusion of textural parameters in urban and forest area image classification improved accuracies of image classification on high-resolution images [4, 10]. Previous investigations have attempted the extraction of tree textures from high-resolution satellite data using neural network, co-occurrence matrix, semi-variogram, threshold-based spatial clustering, local variance, and local maximum filtering [11–16]. Some of these approaches worked well, but the success rate was limited in urban areas. The importance of urban area classification in this region is realized since there is extensive date palm plantation in urban areas throughout Middle Eastern countries. As these trees are planted along the roads, inside and outside private properties and on road side pavements, the gathering of information of these trees for agricultural census purposes is a cumbersome task to achieve, yet there is no systematic database, to document their spatial information.

Researchers started to develop algorithms and application software to count trees [17–19]. In this communication, selective filtering and Laplacian blob [18] are used for classifying date palm trees in both the urban and agricultural areas.

2 MATERIALS AND METHODS

Two Quickbird scenes of April 2005 were selected over the study area (Fig. 1). One of the scenes is over an urban area in central Kuwait, while the other is from an agricultural area in northern Kuwait. The Quickbird data set used is panfused with a spatial resolution of 0.6m.

There are two steps involved in palm tree counting. The first step is the selective smoothing by non-linear diffusion, which results in a sharp contrast among a number of different features followed by Laplacian filtering.

The first step involves the application of a non-linear parabolic equation [20] to the two selected Quickbird scenes. This equation allows selective enhancement and smoothing in addition to simultaneously preventing the blurring of the edges. The processing is quite effective for image classification in urban areas. The equation is stated as

$$\vartheta I(x, y, t)/\vartheta t = g(|Gx\nabla I|)|\nabla I|\,\mathrm{div}\left(\frac{\nabla I}{|\nabla I|}\right), \tag{1}$$

where $|\nabla|\,\mathrm{div}(\nabla I/|\nabla I|)$ diffuses the image $I(x, y)$ in the direction orthogonal to its gradient $|\nabla I|$ and not in all directions. $g(|Gx\,\nabla I|)$ is used for edge enhancements.

This anisotropic filtering is basically the statistical interpretation of the anisotropic diffusion, but it takes slightly more time in processing and implementation [21].

The second step is Laplacian filtering which can be suggested as an irreducible differential invariant. It is expressed mathematically by eqn (2), when a grey scale image defines a first-order derivative as eqn (3) and a second-order derivative by Hessian matrix (eqn(4)).

$$\nabla^2 I = I_{xx} + I_{yy} \tag{2}$$

$$\nabla I = (I_x, I_y) \tag{3}$$

$$H_I = \begin{pmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{pmatrix}. \tag{4}$$

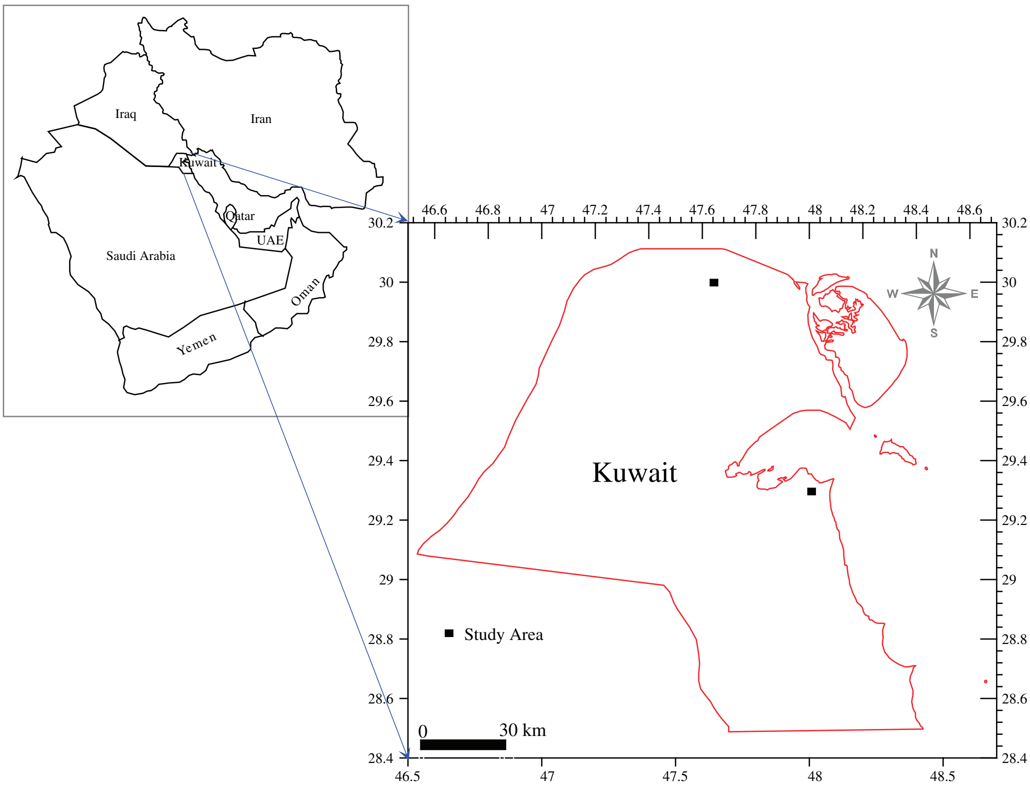

Figure 1: Location map of the study area.

When the second-order derivative is greater than zero and $I_x^2 + I_y^2 = 0$, then the point is referred to as an elliptic point due to its appearance. The sign of Laplacian equation indicates the maxima and minima. The dark blob indicates the minima (Fig. 2a) and the bright blob indicates the maxima (Fig. 2b).

The proposed methodology is morphometric and thus spatial resolution in palm tree mapping is critically important. The use of a 0.6-m spatial resolution data to map palm trees with crown sizes of 3–4 m and intertree spacings of 3–8 m was sufficient.

3 RESULTS AND DISCUSSION

The proposed methodology has been successfully used in the European Union countries for the mapping of olive trees. Application of this methodology to classify date palm trees in arid urban and agriculture areas was employed using two Quickbird scenes (Figs 3 and 4). The original Quickbird scene with different species of trees and bushes with similar spectral characteristics, street and car (Fig. 3a) and the other scene (Fig. 4a) with green houses, building, and trees, is used for classifying using maximum likelihood classification. The results of this classification are not perfect. A simple accuracy assessment was carried out using the random point method in an area of 1000 × 1000 pixels for images 3 and 4.

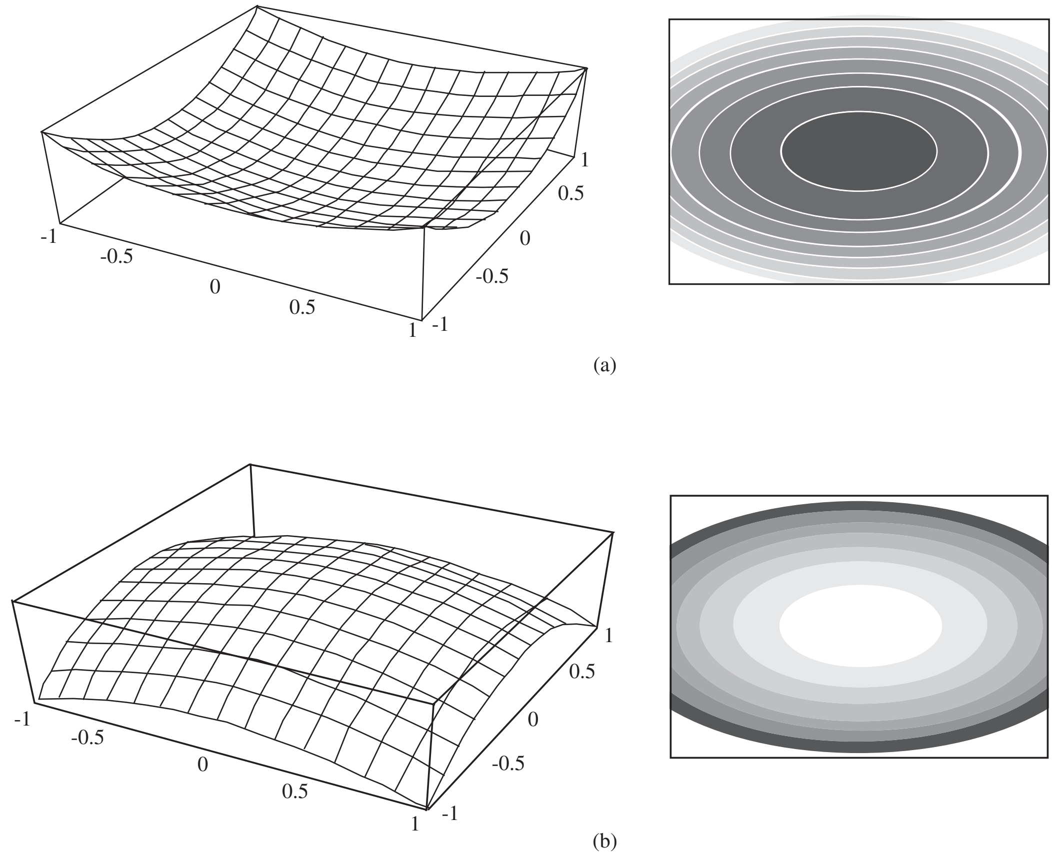

Figure 2: The Laplacian blob: (a) dark blob indicating minima ($I_{xx} + I_{yy} > 0$); (b) bright blob showing maxima ($I_{xx} + I_{yy} < 0$).

A number of 100 randomly selected points were assessed in either image to ascertain whether the pixel was correctly assigned to a class or misassigned to another class in a confusion matrix given in Table 1. The errors are stated as commission and omission errors. Commission error results from incorrect identification of a pixel, while omission error occurs when we simply do not recognize pixel that we should have identified as belonging to a particular class. The Quickbird true colour image was used for visual reference.

The accuracy assessment of the two classifications shows that using the proposed methodology has led to a significant increase in classification accuracies. The accuracy achieved for the maximum likelihood classification is 67% and 79% in urban and peri-urban areas, respectively. Figs 3b and 4b represent the results of the maximum likelihood classification.

The textural characteristics of the trees play a significant role in identification. The smaller area of tree and the similar spectral signatures of grass, play grounds, and lawns make it imperative to integrate textural parameters in classification schemes. In order to achieve this, a selective smoothing procedure was adopted on high-resolution imagery to isolate and characterize individual trees. In the Laplacian maxima filtering, this pre-processing step is crucial since this requires a processing

Table 1: Accuracy of the image classifications.

	Multispectral classification					Laplacian maxima filtering				
	Palm	Non-palm	Omission error (%)	Commission error (%)	Mapping accuracy (%)	Palm	Non-palm	Omission error (%)	Commission error (%)	Mapping accuracy (%)
Urban area										
Palm	68	32	32	33	51.12	97	3	3	5	92.38
Non-palm	33	67	33	32	50.75	5	95	5	3	92.23
Total	101	99			67.5	102	98			96
Peri-urban area										
Palm	82	18	18	24	66.12	99	1	1	3	96.12
Non-palm	24	76	24	18	64.40	3	97	3	1	96.04
Total	106	94			79	102	98			98

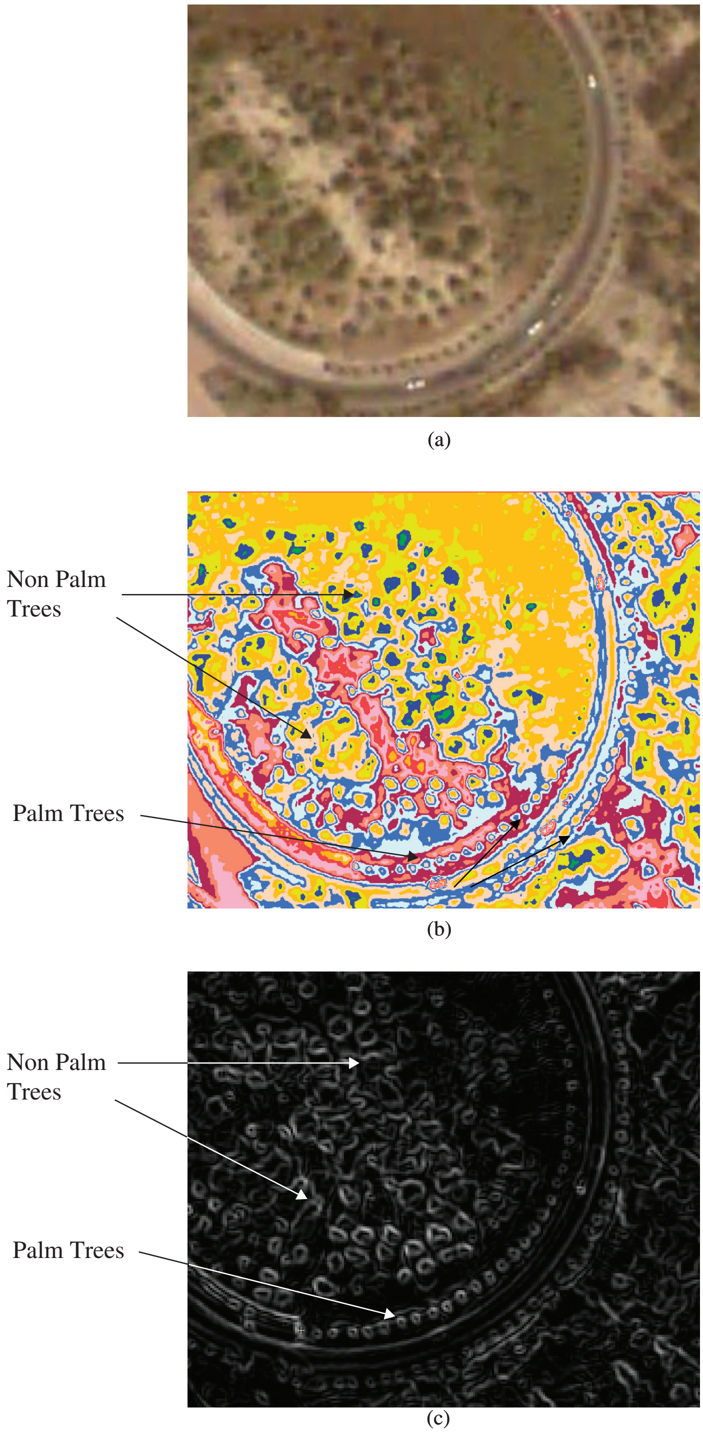

Figure 3: Quickbird data for urban area: (a) original image; (b) maximum likelihood classified image; (c) date palm tree blobs using Laplacian maxima (inverted LUT).

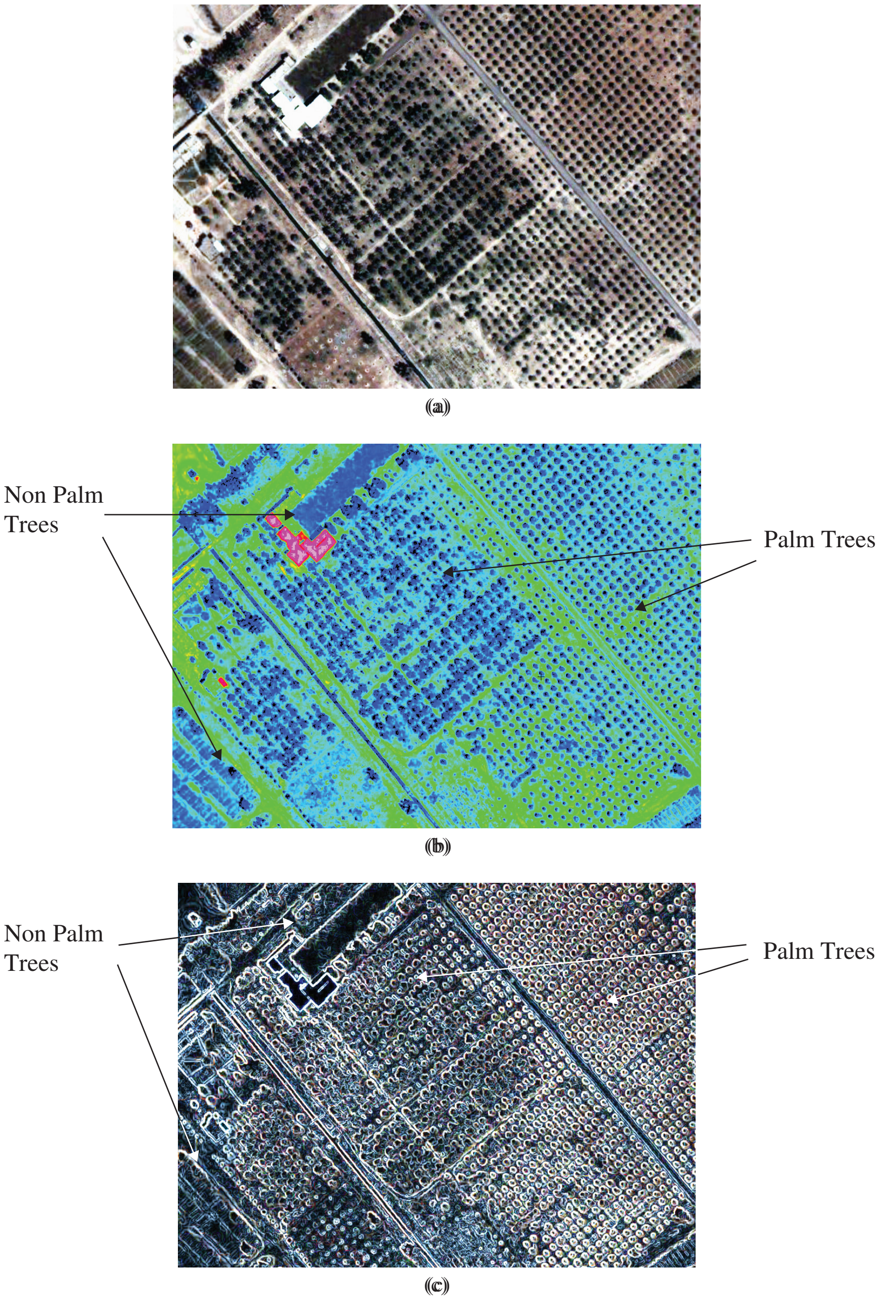

Figure 4: Quickbird data for peri-urban area: (a) original image; (b) maximum likelihood classified image; (c) date palm tree classification using Laplacian blob filtering (inverted LUT).

system to encapsulate the image content. Feature extraction results are directly related to the performance of the initial enhancement and smoothing stage [22–26]. The methodology helped in accurate classification of date palm trees in urban and agriculture areas. An accuracy of 96% is achieved for the urban area (Fig. 3c) and 98% for the agriculture area (Fig. 4c). The advantages of this methodology are clearly the higher accuracies for similar scenes and simple processing. The problems related to shadowing and irregular strands are solved to a larger extent using this approach. The image processing was carried out using PCI geomatica software. However, it is possible to utilize any other software for image processing.

4 CONCLUSIONS

It was demonstrated that the proposed methodology surpasses the conventional maximum likelihood classification in terms of palm tree identification in the study area. The methodology used is precise in palm tree classification in both the urban and agricultural areas. The classification in this instance is simple and straightforward, and the subjective nature of data interpretation, which relies a great deal on the interpreter's perception, is greatly minimized. These high accuracies in classification are also due to the fact that there is no tree undergrowth and the uniformity of palm tree crown sizes.

The analyses show that the palm trees are highlighted as blobs and the crown patterns are very clearly segregated from other vegetation types in the area. The Laplacian blob maxima coincide with the centre of the tree. The success of the blob detection technique in spatial mapping of palm trees in urban areas of Kuwait encourages us to promote this methodology for palm tree counting in Middle Eastern countries.

ACKNOWLEDGEMENTS

Authors are thankful to the Kuwait Institute for Scientific Research for providing funds for project EM030K. Suggestions and remarks of Professor John R. Jensen, Department of Geography, University of South Carolina, Columbia, SC, USA, are thankfully acknowledged.

REFERENCES

[1] Sawaya, W.N., Dates of Saudi Arabia. Regional Agriculture and Water Research Center. Ministry of Agriculture and Water, Riyadh, Saudi Arabia, 1986.

[2] Anonymous, The cherished date palm. Available at: http://www.saudiembassy.net/Publications/MagWinter97/date-palm.htm, 1997.

[3] Anonymous, Al Madina Al Munawarah Date Company. Available at: http://tomoor.com/?page=shop/date_palm_trees, 2004.

[4] Zang, Y., Texture – integrated classification of urban treed areas in high resolution color infrared imagery. *Photogrammetric Engineering and Remote Sensing*, **67(12)**, pp. 1359–1365, 2001.

[5] Barnsley, M.J., & Barr, S.L., Inferring urban land use from satellite sensor images using kernel-based spatial reclassification, *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 949–958, 1996.

[6] Gao, J. & Skillcorn, D., Capability of SPOT XS data in producing detailed land cover maps at the urban-rural periphery. *International Journal of Remote Sensing*, **19**, pp. 2877–2891, 1998.

[7] EEC, Decision No. C (97)2690. Decision of commission of the financing of an action concerning counting of the number of Olive trees in member states, 1997.

[8] Howard, J.A., *Remote Sensing of Forest Resources*, Chapman and Hall: London, 1991.

[9] Marceau, D.J., Gratton, D.J., Fournier, R.A., & Fortin, J.P., Remote sensing and the measurement of geographical entities in a forested environment. 2. The optimal spatial resolution. *Remote sensing of Environments*, **49(2)**, pp. 105–117, 1994.

[10] Woodcock, C.E. & Strahler, A.H., The factor of scale in remote sensing. *Remote Sensing of Environment*, **21**, pp. 311–332, 1987.

[11] Dreyer, P., Classification of land cover using optimized neural nets on spot data. *Photogrammetric Engineering and Remote Sensing*, **59**, pp.–621, 1993.

[12] Anys, H., Bannari, A., He, D.C. & Morin, D., Texture analysis for the mapping of urban areas using airborne MEIS-II images. *Proc. 1st International Airborne Remote Sensing Conference and Exhibition*, Strasbourg, France, Vol. 3, pp. 231–245, 1994.

[13] St-Onge, B.A. & Cavayasm F., Automated forest structure mapping from high resolution imagery based on directional semivariogram estimates. *Remote Sensing of Environment*, **61**, pp. 82–95, 1997.

[14] Culvenor,D.S., Coops, N., Preston, R. & Tolhurst, K., A Spatial clustering approach to automated tree crown delineation. *Proceedings of the International Forum on Automated Interpretation of High Spatial Resolution Digital Imagery for Forestry*, 10–12 February, Victoria, BC, Canada, Natural Resources Canada, pp. 67–80, 1999.

[15] Coops, N., & Culvenor. D., Utilizing local variance of simulated high spatial resolution imagery to predict spatial pattern of forest strands. *Remote Sensing of Environment*, **71**, pp. 248–260, 2000.

[16] Wulder, M., Niemann, K.O. & Goodenough, D.G., Local maxima filtering for the extraction of tree locations and Basdal Area from high spatial resolution imagery. *Remote Sensing of Environment*, **73**, pp. 103–114, 2000.

[17] Granlund, G.H., The complexity of vision. *Signal Processing*, **74**, pp. 101–126, 1999.

[18] Kay, S., Leo, O., Peedel, S. & Giardino, G., Computer assisted recognition of olive tree in digital imagery. Space Applications Institute JRC of the European Commission, Ispra, Italy, 2000.

[19] Karantzalos, K., Combining anisotropic diffusion and alternating sequential filtering for satellite image enhancement and smoothing. *Proceedings International Conference of Image and Signal Processing for Remote Sensing IX*, SPIE, Barcelona, Spain, 2003.

[20] Alvarez, L., Lions, P.L. & Morel, J.M., Image selective smoothing and edge detection by non linear diffusion. *SIAM Journal of Numerical Analysis*, **29**, pp 845–866, 1992.

[21] Black, M.J. & Sapiro, G., Robust anisotropic diffusion filtering. *IEEE Transactions on Image Processing*, **7(3)**, pp. 421–432, 1998.

[22] Argialas, D. & Harlow, C., Computational image interpretation models – an overview and a perspective. *Photogrammetric Engineering and Remote Sensing*, **56(6)**, pp. 871–886, 1990.

[23] Adelmann, H.G., An edge sensitive noise reduction algorithm for image processing. *Computers in Biology and Medicine*, **29**, pp. 137–145, 1999.

[24] Gulch, E., Digital systems for automated cartographic feature extraction. *International Archive of Photogrammetry and Remote Sensing*. Amsterdam, Vol. 33, Part B2, pp. 241–256, 2000.

[25] Mikhail, E.M., Multi source feature extraction and visualization in urban environments. *International Archives of Photogrammetry and Remote Sensing*, Amsterdam, Vol. 33, Part B3, pp. 592–607, 2000.

[26] Karantzalos, K. & Argialas, D., Evaluation of selected edge detection techniques in remotely sensed images. *Proceedings of the International Conference on Image and Signal Processing for Remote Sensing VI*, Crete, Greece, 2002.