A NOTE ON DIFFERENCE SPECTRA FOR FAST EXTRACTION OF GLOBAL IMAGE INFORMATION.

B.J van Wyk* M.A. van Wyk* and F. van den Bergh**

** French South African Technical Institute in Electronics (F'SATIE) at the Tshwane University of Technology, Private Bag X680, Pretoria 0001.*
*** Remote Sensing Research Group, Meraka Institute, CSIR, Meiring Naude Drive, Pretoria, South Africa.*

Abstract: The concept of an *Image Difference Spectrum,* a novel tool for the extraction of global image information, is introduced. It is shown that *Image Difference Spectra* are fast alternatives to granulometric curves, also referred to as pattern spectra. *Image Difference Spectra* are computationally easy to implement and are suitable for real-time applications.

Key words: Feature Extraction, Granulometries, Pattern Spectra

1. INTRODUCTION

Granulometries are useful tools for image analysis due to their ability to characterize size distributions and shapes and have been used extensively for feature extraction for classification, segmentation and texture analysis [1, 2]. Traditionally, granulometries are obtained using a series of openings or closings with convex structuring elements of increasing size. The granulometric analysis of an image results in a *signature* of the image with respect to the granulometry used which is referred to as granulometric curve or pattern spectrum. Due to the computational load associated with the calculation of granulometries, Vincent [3, 4], building on the work of Haralick *et al.* [2], proposed fast and efficient granulometric techniques using linear openings.

The *Image Difference Spectrum* algorithm proposed in this paper is not a morphological algorithm, but *similar* to morphological pattern spectra, the proposed algorithm extracts size distributions which can be used as global image features for a variety of pattern recognition applications.

2. IMAGE DIFFERENCE SPECTRA

The idea behind an *Image Difference Spectrum* is compactly summarised by the following three definitions:

Definition 1: An *Image Difference Spectrum*, Ω, is defined as a normalized representation of the number of occurrences of the lengths of *Segments of Increase* in each line of a greyscale image, Φ, having N rows indexed by n, and M columns indexed by m.

Definition 2: A *Segment of Increase* is a group of consecutive samples in a row of an image Φ, such that $\Phi(n,m+1)-\Phi(n,m) > \Phi(n,m)-\Phi(n,m-1)-\varepsilon$, where $\varepsilon \geq 0$ is a *Spectral Slack Parameter*.

Let Ω_i, $i=1,...,C$, be the *Image Difference Spectra* for C different classes. The *Spectral Slack Parameter,* ε, is a positive parameter chosen to maximize some norm between all Ω_i.

Unlike granulometric pattern spectra algorithms, the *Image Difference Spectrum* algorithm, given by the pseudo code in section 3, is extremely easy to implement and has a linear complexity directly proportional to the number of pixels in the greyscale image:

3. PSEUDO CODE

initialize $k \leftarrow 0, \quad \tilde{\Delta} \leftarrow 0, \quad \Omega \leftarrow \mathbf{0}$
for $n = 1:N$
    for $m = 1:M$
        $\Delta \leftarrow \Phi(n,m) - \Phi(n,m-1)$
        if $\Delta > \tilde{\Delta} - \varepsilon$, increment k
        else, increment $\Omega(k)$ and set $k \leftarrow 0$
        end if
        $\tilde{\Delta} \leftarrow \Delta$
    end for
end for
scale Ω by dividing each element by the total number of pixels, i.e. $\frac{\Omega(k)}{NM} \forall k$.

4. EXPERIMENTAL RESULTS

The *Difference Spectrum* and Vincent's *Linear Greyscale Pattern Spectrum* [4] have been used to classify greyscale QuickBird satellite images over Soweto as formal suburbs or informal settlements. Since Vincent has demonstrated, using a variety of image applications, that *Linear Greyscale Pattern* spectra are faster and just as useful as conventional pattern spectra, only *Linear Greyscale Pattern Spectra* have been considered for comparison. The experimental results were obtained using MATLAB© code running on a 2 GHz Intel Core 2 Duo processor PC with 2GB RAM.

Only the first 10 bins of the spectra derived from the training and test sets, were used as the input to two feed forward neural networks, each having a single hidden layer with 6 neurons, trained using the Levenberg-Marquardt back-propagation algorithm. In fact, the *Image Difference Spectra* bins can be limited to only the first three without a degradation in performance.

A hundred images from selected Soweto suburbs, labelled by a built environment expert from the South African *Centre for Scientific and Industrial Research*, were equally divided into a training set and a test set. For all images *N=M=200.* Refer to Figures 1 and 2 for random image selections from the *formal suburb* and *informal settlement* training sets and their associated *Image Difference Spectra* and un-scaled *Linear Greyscale Pattern Spectra.*

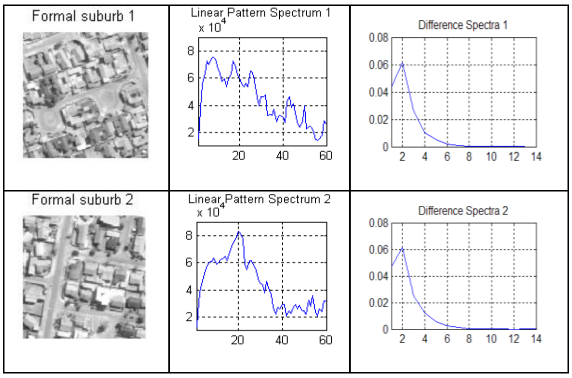

Figure 1: Soweto formal suburb images with their associated un-scaled *Linear Pattern Spectra* and scaled *Image Difference Spectra*.

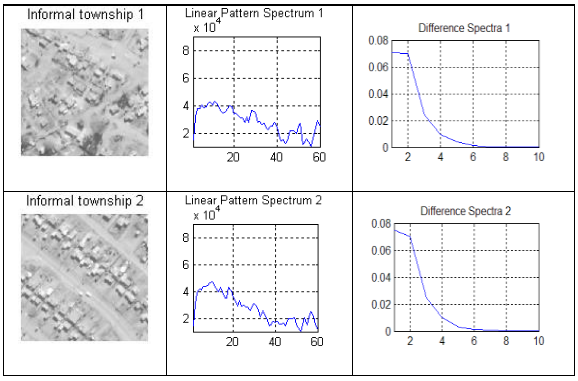

Figure 2: Soweto informal settlement images with their associated un-scaled *Linear Pattern Spectra* and scaled *Image Difference Spectra*.

For each of the two classes there were 25 training images and 25 test images. Using the Euclidean norm, a *Spectral Slack Parameter* of 3, was found experimentally to be optimal for the training set. For both algorithms a training and testing accuracy of 100% were achieved. The *Image Difference Spectrum* on average executed in 0.39 seconds and the *Linear Greyscale Pattern Spectra* on average in 1.11 seconds for a structuring element (which determines the number of bins) of 10. Calculating the *Linear Greyscale Pattern Spectra* using a structuring element of 60 took on average 14.15 seconds. Note that the number of bins for the *Image Difference Spectrum* are determined by the image characteristics and is not a parameter that can be selected.

5. CONCLUSION

A novel algorithm for the extraction of global image information was proposed and its application to the classification of images were presented. From the results obtained, it is clear that for the specific application considered, it performed well, both in terms of accuracy and computational speed. The algorithm has also been applied to the classification of seed mixture and steel surface images with equal success. The proposed algorithm can be used as a fast and robust alternative to granulometric pattern spectra.

6. REFERENCES

[1] P. Maragos, ‘Pattern spectrum and multiscale shape representation’, *IEEE Transactions on Pattern Analysis and Machine intelligence,* Vol. 11, No. 7, pp. 701-716, 1989.

[2] R. M. Haralick, S. Chen and T. Kanungo, ‘Recursive opening transform’, *in Proceedings of the IEEE International Computer Vision and Pattern Recognition Conference CVPR’92,* Champaign, IL, USA, pp. 560-565, 1991.

[3] L. Vincent, ‘Granulometries and opening trees’, *Fundamenta Informaticae*, Vol. 41, pp. 57-90, 2000.

[4] L. Vincent (1994) Fast grayscale granulometry algorithms, In Serra J. and Soille P. editors, *EURASIP Workshop ISMM’94: Mathematical Morphology and its Applications to Image Processing,* pp. 265-272, Fontainebleau, France, Kluwer Academic Publishers, 1994.

This work was financially supported by the Tshwane University of Technology (TUT) and the NRF under grant TRD2005070100036. Ignace T Toudjeu is thanked for implementing Luc Vincent’s linear algorithm. The authors would also like to thank "Satellite image: DigitalGlobe" for assisting with the QuickBird image over Soweto.