Global Image Feature Extraction Using Slope Pattern Spectra

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Abstract. A novel algorithm inspired by the integral image representation to derive an increasing slope segment pattern spectrum (called the Slope Pattern Spectrum for convenience), is proposed. Although many pattern spectra algorithms have their roots in mathematical morphology, this is not the case for the proposed algorithm. Granulometries and their resulting pattern spectra are useful tools for texture or shape analysis in images since they characterize size distributions. Many applications such as texture classification and segmentation have demonstrated the importance of pattern spectra for image analysis. The Slope Pattern Spectra algorithm extracts a global image signature from an image based on increasing slope segments. High Steel Low Alloy (HSLA) steel and satellite images are used to demonstrate that the proposed algorithm is a fast and robust alternative to granulometric methods. The experimental results show that the proposed algorithm is efficient and has a faster execution time than Vincent's linear granulometric technique.

Keywords: Pattern spectra, feature extraction, texture analysis, integral image.

1 Introduction

Traditionally, granulometries are obtained using a series of openings or closings with convex structuring elements of increasing size. Granulometries constitute a useful tool for texture and image analysis since they are used to characterize size distributions and shapes [1], [2]. The granulometric analysis of an image results in a signature of the image with respect to the granulometry used which is referred to as a granulometric curve or pattern spectrum. Granulometric curves are used as feature vectors [3] for applications such as segmentation [4] and texture classification [5]. For example [6], granulometries based on openings with squares of increasing size as structuring elements, were used to extract dominant bean diameter from binary images of coffee beans. Granulometries were also used to estimate the dominant width of the white patterns in the X-ray images of welds [7]. Due to the computational load associated with the calculation of granulometries, Vincent [6], building on the work of Haralick et al. [2], proposed fast and efficient granulometric techniques using linear openings.

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In this paper, a novel algorithm inspired by the idea of an integral image, to derive increasing slope segment pattern spectra (referred to as Slope Pattern Spectra in the sequel), is proposed and compared to Vincent's linear granulometric technique in terms of speed of execution and classification accuracy. The Slope Pattern Spectra algorithm is not a morphological algorithm but similar to morphological granulometries, the proposed algorithm extracts global image information in the form of pattern spectra.

The layout of this paper is as follows. Section 2 summarizes the concept of morphological granulometries with reference to the linear granulometries proposed by Vincent [6]. The proposed Slope Pattern Spectra algorithm is described in Section 3. Experimental results are presented in Section 4. Future work and the conclusion are given in Section 5.

2 Mathematical Morphology and Grayscale Granulometries

This section introduces the basic principles of mathematical morphology and grayscale granulometries to facilitate the understanding of the granulometric techniques and how they differ with respect to the proposed algorithm. Image-based mathematical morphology is a general method for processing images based on set theory. Images are presented as a set of points or pixels on which operations such union and intersection are performed [8]. It was pioneered by Matheron [9] and Serra [10] at the Ecole des Mines de Paris in Fontainebleau in 1964. The first algorithms were derived for 2D binary images, but were later extended to grayscale images. Two basic morphological operations are dilation and erosion [10]. In general, dilation causes objects in the image to dilate or grow in size. On the contrary, erosion causes objects to shrink. The amount of growth or shrinkage is a function of the chosen structuring element.

Using the extremum [11] grayscale dilation is defined by $\delta_B(f)(x) = \max_{b \in B} f(x+b)$ and grayscale erosion by $\varepsilon_B(f)(x) = \min_{b \in B} f(x+b)$ with f be a grayscale image and B a structuring element. Dilation and erosion (either binary or grayscale) are combined to derive two more advanced morphological operations called opening and closing. An opening is when erosion is performed, followed by dilation. The reverse is referred to a closing. These operations, often referred as morphological filtering, are the building blocks of powerful image processing tools for structural and texture analysis [12], [5]. One such a tool, derived from size distributions of objects in the image, is the granulometric curve or pattern spectrum. Computing granulometric operations is comparable to a sieving process where particles are sieved through sieves of different sizes and shapes. Particles smaller than the structuring element are removed. A morphological pattern spectrum is defined as the rate of sieving and can be seen as a unique signature of an image. For more detailed information on granulometries, viewed as morphological filters involving sequences of opening or closing to extract global information in the image [10], the reader is referred to Dougherty [13] and [14], Maragos [1] and Vincent [6].

Due to the computational load associated with the calculation of traditional morphological granulometries, Vincent [6] and [7], building on the work of Haralick et al. [2], proposed fast and efficient granulometric techniques using linear openings where a line segment is used as a structuring element. For more information on linear grayscale granulometries the reader is referred to Vincent [6] and [7].

3 Slope Pattern Spectra

The Slope Pattern Spectra algorithm is not a morphological algorithm, but similar to morphological or linear granulometries [6], the proposed algorithm extracts a type of size distribution in the form of a pattern spectrum, a powerful global image feature vector which can be interpreted as a type of histogram. The algorithm was inspired by an intermediate image representation, called an integral image [15] used to rapidly compute features generally referred to as "summed area tables" by Crow [16] and Lienhard and Maydt [17].

In the formulation presented here, a row or sub-row of a grayscale image is defined as a line segment. In this paper the Slope Pattern Spectrum algorithm applies the integral image technique to horizontal line segments to obtain integral horizontal line segments.

Definition 1 (Horizontal line segment)
A horizontal line segment S, *of length* $l(S)$, *is defined as a set of pixel values* $\{p_0, p_1, \ldots, p_{n-1}\}$ *in a horizontal line (i.e. a row) of an image* f, *such that for* $0 < i < n$, $S(i) = p_i = N_r(p_{i-1})$ *i.e.* p_i *is the neighbor of* p_{i-1} *to the right, implying that the set of pixel values is ordered.*

Definition 2 (Integral horizontal line segment)
An integral horizontal line segment F, *of length* $l(F) = n$, *of a horizontal line segment* $S = \{p_0, p_1, \ldots, p_{n-1}\}$, *is defined as*

$$F(i) = \sum_{k=0}^{i} S(k), \quad for\ 0 \le i < n, \tag{1}$$

implying that

$$F(i) \le F(N_r(p_i)), \quad for\ 0 \le i < n-1. \tag{2}$$

From Definition 2 it is clear that the value of a neighbor to the right is the sum of all left neighbor values. The values of the integral horizontal line segment are therefore monotonically increasing as we move towards the right. From the integral horizontal line segment it is also evident that the difference between a value and its left neighbor is always greater than or equal to zero. This variation can be seen as a discrete derivative function:

Definition 3 (Integral segment derivative)
ΔF, *the integral segment derivative, is defined as*

$$\forall 0 \le i \le n-2, \quad \Delta F(i) = F(N_r(p_i)) - F(i). \tag{3}$$

This representation of the variation of values on the integral horizontal line segment leads to the following definition of a slope segment:

Definition 4 (Slope segment)
A slope segment, denoted by SS, *of length* $l(SS) = n$, *is an integral horizontal line segment such that*

$$\forall\, 0 \le i < n-2\,, \qquad \Delta F(i) \le \Delta F(i+1)\,, \tag{4}$$

or

$$\forall\, 0 \le i < n-2\,, \qquad \Delta F(i) \ge \Delta F(i+1)\,. \tag{5}$$

Definition 4 corresponds to two types of slope segments. Equation 5 is defined as a decreasing slope segment DSS and Equation 4 as an increasing slope segment ISS .

By comparing different slope segments, an increasing slope segment is therefore identified as the slope segment which represents an increasing variation in terms of integral values between two consecutive pixel locations. Multiple increasing slope segments can also be identified from an integral line. The quantification of an increasing slope segment in a horizontal line of an image is given by Definitions 5 and 6:

Definition 5 (Measure of an increasing slope segment)
Define $m(ISS)$ to be a measure of an increasing slope segment as

$$m(ISS) = \sum_{i=0}^{n-2} \Delta F(i)\,. \tag{6}$$

Since Equation 6 is a telescoping sum it immediately follows that

$$m(ISS) = F(N_r(p_{n-2})) - F(0) = F(n-1) - F(0)\ . \tag{7}$$

Definition 6 (Contribution of an increasing slope segment)
The contribution of the increasing slope segment to the n^{th} bin of the increasing slope pattern spectrum $PS_{ISS}[n]$ is $\frac{m(ISS)}{n}$, where $n = l(ISS)$ is the length of the increasing slope segment.

As will become evident in the next section, the *Increasing Slope Pattern Spectra* will have *N* bins, where *N* is determined by the length of identified *increasing slope segment* in the image being analyzed.

3.1 Proposed Algorithm

Based on the above definitions, the principle of the proposed algorithm is as follows: Consider a grayscale image *f* where horizontal lines of f (rows of f) are considered one after the other, and scanned from left to right. In each horizontal line, possible slope segments SS are determined. If the slope segment is an increasing slope segment (ISS), the measure of the increasing slope segment divided by its length, $\frac{m(ISS)}{n}$, is calculated, and the n^{th} bin of the pattern spectra incremented with this value. If the lengths of the increasing slope segments determined at different horizontal lines are equal, the same pattern spectrum bins are respectively incremented by $\frac{m(ISS)}{n}$. These operations are repeated until the last horizontal line of f is processed. This proposed algorithm for the grayscale image f is presented by Algorithm 1.

Algorithm 1: Slope Pattern Spectra algorithm

Initialization:
Pattern spectrum: for all $n>0$, $PS[n]\leftarrow 0$
Calculation:
for each horizontal line (row) of the grayscale image f
  Initial integral pixel value: $F(0)\leftarrow 0$
  Length of ISS : $l(ISS)\leftarrow 0$
  $\Delta\tilde{F}\leftarrow 0$
  for each pixel value p_i in the horizontal line with $i\geq 1$ do:
   $F(i)\leftarrow F(i-1)+p_i$ i.e. the integral image;
   $\Delta F(i)\leftarrow F(i)-F(i-1)$ i.e. the integral segment derivative;
    if $\Delta F(i)\geq\Delta\tilde{F}$
     $l(ISS)\leftarrow l(ISS)+1$ i.e increase length of the ISS ;
     $\Delta\tilde{F}\leftarrow\Delta F(i)$;
    else
     $n\leftarrow l(ISS)$ i.e. determine the length of the ISS ;
     $m(ISS)=F(i-1)-F(i-n-1)$ i.e. determine the measure of ISS ;
     $PS[n]\leftarrow PS[n]+\frac{m(ISS)}{n}$ i.e. add the contribution of ISS to n^{th} bin of the SPS ;
     $\Delta\tilde{F}\leftarrow 0$;
     $l(ISS)\leftarrow 0$;
    end if
  end for
end for.

In the next section, regression (characterization) and classification experiments, where the resultant *Slope Pattern Spectra* are used in conjunction with neural networks, are presented.

4 Experimental Results

Two classification and regression experiments were carried out to demonstrate the usefulness of the pattern spectra derived from the proposed algorithm, and to compare the performance of the Slope Pattern Spectra algorithm to that of granulometric techniques. A disk and a horizontal line segment were used as structuring elements for the morphological and the linear grayscale granulometries respectively. All sample images used here are 256 x 256 pixels, except for the QuickBird images which are 200 x 200 pixels. The experimental results presented were obtained using MATLAB code running on a personal computer Intel Pentium 4 with a CPU speed of 2.66 GHz and 256 MB RAM.

4.1 Steel Image Regression

Images of High Steel Low Alloy sample were used in this application. The steel samples were prepared as part of a study by the department of Chemical and Metallurgical Engineering at the Tshwane University of Technology to determine the effect on the microstructure of the steel, when laser instead of mechanical forming is used. Flat pieces of the high strength steel micro-alloyed with 0.03wt%Nb(Niobium), having a thickness of 3.5 mm, were laser treated using a 1kW CO_2 laser with an 8 mm diameter beam. Five laser scans were applied per cycle and each sample was treated with a total of 13 cycles (i.e. a laser treated region). These sections were sectioned using a cut-off machine, and polished using standard metallographic methods. These samples were viewed under a microscope with a magnification factor of 200% and recorded using a digital camera. Each pair of samples were recorded at depths of *0.2917mm*, *0.5834mm*, *0.8751mm*, *1.1668mm*, *1.4585mm*, *1.7502mm*, *2.0419mm*, *2.3336mm*, *2.6253mm*, *2.9170mm*, *3.2087mm* and *3.5004mm*, giving a total of 24 samples. Some of the sample images corresponding to different depths are shown in Fig. 1.

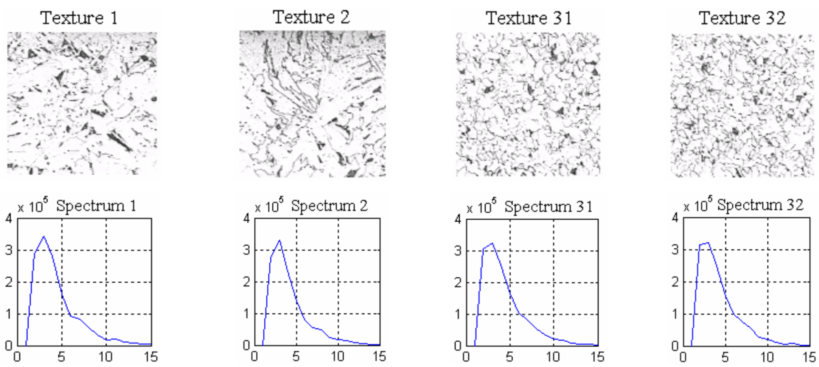

Fig. 1. Examples of four HSLA sample images Texture 1, 2, 31 and 32) and their un-scaled slope pattern spectra (Spectrum 1, 2, 31 and 32) respectively

An RBF approximation neural network, known as a good neural network for implementing and modeling any continuous input-out mapping in supervised applications [18], was used in this experiment to approximate the depth of an HSLA sample, which is a continuous value. Gaussian radial basis function neurons were used with linear output neurons. The training set and the target vectors (depths, corresponding to each pattern spectrum in the training set), were used to train the RBF network. The performance measures for different types of pattern spectra during testing are shown in Table 1. The performance of the RBF network for different feature extraction techniques was measured in terms of the Mean Squared Error (MSE), which is the mean of the squared difference between the target vector (expected depths) and the actual outcome (approximated depths) given by the RBF network.

Table 1. Performance measures for regression (characterization)

Features	Morphological Pattern Spectra	Linear Pattern Spectra	Slope Pattern Spectra
Minimum pattern length	*14*	*36*	*14*
Mean squared error	*0.0780*	*0.2088*	*0.1201*

Good results for all type of pattern spectra were obtained since their mean squared errors are low. Table 1 only shows the MSE for minimum pattern length, i.e. the minimum pattern length giving the best results (i.e. increasing the length beyond this value did not improve performance). Contrary to the classification result, the performance expressed in means squared error is different with respect to the type of pattern spectra used. The results in Table 1 give an indication of the discriminative power of each pattern spectra technique.

4.2 Soweto Satellite Image Classification

The Slope Pattern Spectrum and Vincent's Linear Grayscale Pattern Spectrum [6] have also been used to classify grayscale QuickBird satellite images over Soweto as formal suburbs or informal settlements. Since Vincent has demonstrated, using a variety of image applications, that Linear Pattern spectra are faster and just as useful as conventional pattern spectra, for this experiment only Linear Pattern Spectra have been considered for comparison. Only the first 14 patterns 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 3 neurons, trained using the classical back-propagation algorithm. Further experimentation revealed that the Image Slope Spectra patterns can be limited to only the first seven with a minimum of two neuron at hidden layer without a degradation in performance.

A hundred images from selected Soweto suburbs, labeled by a built environment expert from the South African Council for Scientific and Industrial Research, were equally divided into training and test sets. All images were of size 200 x 200. Refer to Fig. 2 and Fig. 3 for random image selections from the formal suburb and informal settlement training sets and their associated Slope Pattern Spectra and unscaled Linear Pattern Spectra. For each of the two classes there were 25 training images and 25 test images. For both algorithms a training and testing accuracy of 100% were achieved.

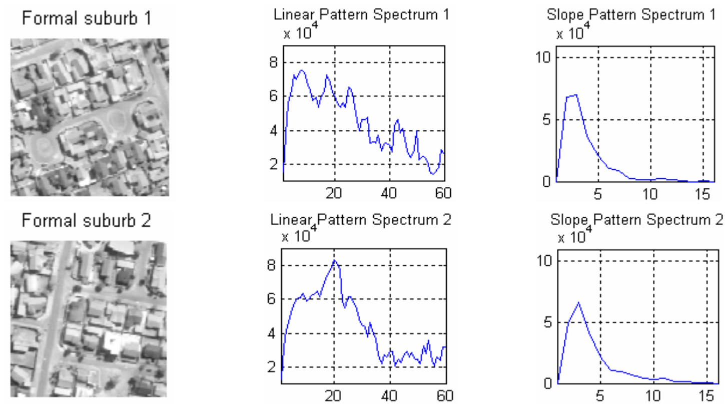

Fig. 2. Example of *formal suburb* settlement and their corresponding linear and slope pattern

4.3 Execution Time

The execution time of each sample was calculated using the MATLAB commands 'tic' and 'toc' during computation as the average time of ten runs when computing the pattern spectrum. The speed of execution was evaluated by means of ratio calculated as the execution time to compute the *linear pattern spectrum* divided by the execution time of the proposed algorithm. Typically ratios of 120 and 124 were obtained for Texture and Formal suburb images respectively showing that the proposed algorithm is two orders of magnitude faster than the linear granulometry, making it an ideal candidate for real-time implementation.

Though morphological pattern spectra potentially have more descriptive power, and produced good results for both experiments, execution time remains excessive. The speed of the proposed algorithm is mainly due to the fact that the proposed algorithm is a single pass algorithm.

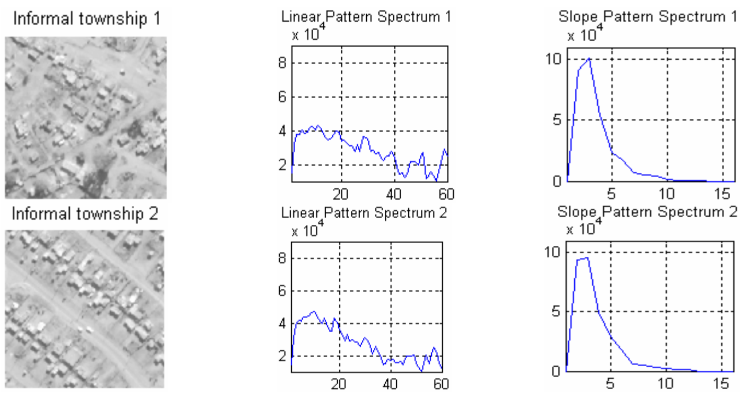

Fig. 3. Example of *informal township* settlements and their corresponding linear and slope pattern

5 Conclusion

A novel algorithm was proposed in this paper and its application to the classification of satellite images and the characterization of laser-treated HSLA samples, were presented. From the results obtained it is clear that for the specific applications considered, it performed well, both in terms of accuracy and computational speed. It can be concluded that the proposed algorithm is an efficient and accurate way to extract global image features from a grayscale image.

Although decreasing slope segments were not used in this paper, future developments will explore their ability to extract information from a given grayscale image in the form of pattern spectra. It will also be very interesting if the slope distribution can be defined as Euclidean openings so that the proposed technique can satisfy the properties of granulometries. Extensions to colour images are also under consideration.

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