COLOUR FRACTAL DIMENSION FOR PSORIASIS IMAGE ANALYSIS

Alexandru CĂLIMAN[†], Mihai IVANOVICI[†], Noël RICHARD[‡]

[†]MIV Imaging Venture Laboratory
Department of Electronics and Computers,
Transilvania University
Braşov, România
[‡]XLIM-SIC UMR CNRS 6172
Signals, Images and Communications
University of Poitiers, Poitiers, France

ABSTRACT

In the context of a medical application for dermatology, we propose a colour image segmentation approach based on the colour fractal dimension as local feature. For the estimation of the fractal dimension we use the extension to the colour domain of the probabilistic box-counting algorithm. This approach is defined in the RGB colour space, using the Minkowski infinity norm. We compare our obtained results on colour images of psoriatic lesions with the results given by the most used segmentation techniques. We present our experimental results and a discussion on the effects of the tunable parameters that characterize the approach, then we conclude the paper.

Keywords: *Colour Image Segmentation, Fractal Dimension, Colour Texture, Psoriasis, Medical Imaging*

1. INTRODUCTION

The segmentation operation is probably the most difficult task in image processing, mainly due to the fact that it's an open-loop technique, therefore the resulting segmentation map cannot be refined by an iterative approach. In addition, the result can only be correctly judged by the human expert, and compared to a so-called "ground truth", i.e. a reference hand-segmented image. However there are metrics used to assess the quality of a segmentation [1]. There are mainly two ways to tackle the problem of segmentation: contour-based and region-based [2]. The contour extraction methods are mainly Laplace-based and the *de facto* approach is considered to be Canny [3], the most refined one of them. For the region-based segmentation there exist several major approaches: the JSEG [4], watershed [5] and pyramidal decomposition [6]. However, there are also newer approaches on image segmentation like turbo pixel decomposition [7], graph cuts [8] and CSC segmentation [9]. In the last decades great achievements in image segmentation based on local feature extraction were made. This feature can be: statistical moments [10], invariants [11], texture features like correlograms [12] and co-occurrence matrix [13], and fractal features i.e. fractal dimension and lacunarity, the two widely-used multi-scale complexity measures.

The fractal geometry, introduced by B. Mandelbrot in 1983, is used to characterize self-similarity in sets called fractals. These sets are impossible to describe using the classical geometry [14] due to their complexity, "chaotic" representation or due to their recursive definition. Fractal dimension, is a measure that characterize the complexity of a fractal set. By indicating how the fractal fills the space, the fractal dimension can be used as an indicator for whether texture-like surfaces belong to a class or another. Therefore, for this reason and due to its invariance to scale, rotation or translation it is successfully used for classification and segmentation. Lacunarity is a mass distribution function indicating how the space is occupied [15]. The fractal geometry is used in extremely wide area of applications such as in finance and stock market, quality of food analysis and medical applications [16, 17].

2. FRACTAL DIMENSION ESTIMATION

The fractal dimension is a real number that gives an indication of how much space is filled by a fractal. There are many specific definitions of fractal dimension, however the most important theoretical dimensions are the Hausdorff dimension [18] and the Renyi dimension [19]. These dimensions are not used in practice, due to their definition for continuous objects. However there are several expressions which are directly linked to the theoretical ones and whose simple algorithmic formulations make them very popular.

An approximation of the Hausdorff dimension is the box-counting dimension, also referred as Minkovski-Bouligand [18], given by $D_{box} = -\frac{logN_\delta}{log\delta}$, where N_δ is the number of boxes of size δ needed to cover the given fractal set. This formula can be easily applied on grayscale images modeled as a discrete surface or function $z = f(x,y)$, where z is the luminance at the (x,y) coordinates of the image. In this case the box-counting algorithm consists on counting the boxes which cover the entire surface, starting from small-size boxes towards large sized ones. The fractal dimension equals the slope of the regression line through the points $(log(\delta), -logN(\delta))$.

The Voss algorithm is a probabilistic particularization of the box-counting algorithm [20]. The arrangement of the fractal set is characterized by the probability matrix $P(m,\delta)$ which is the probability that m points to be inside a δ-sized cube (box). If we consider that the total number of points in the image is M, the number of boxes that contain m points is $N(m,\delta) = \frac{M}{m}P(m,\delta)$.

Therefore, the total number of boxes needed to cover the image is

$$\langle N(\delta)\rangle = \sum_{m=1}^{N} \frac{M}{m} P(m,\delta) = M \sum_{m=1}^{N} \frac{1}{m} P(m,\delta) \qquad (1)$$

which results in

$$N(\delta) = \sum_{m=1}^{N} \frac{1}{m} P(m,\delta) \propto \delta^{-D} \qquad (2)$$

where D is the fractal dimension. Practically, for a certain cube centered in a pixel, the number of pixels that fall inside the cube is counted. This number of pixels depending on the box size for the entire image is then represented in a log-log space and the slope of the regression line resulted from these points represents an estimate of the fractal dimension.

In the case of color images, the approach is approximately the same by considering each value $z = f(x,y) = (r,g,b)$, therefore the image being a discrete hyper-surface in the 5-dimensioal space. The box-counting algorithm uses the infinite order norm Minkowski distance, in RGB color space, which is suitable for this approach. A more detailed description of this algorithm applied on color fractal images can be found in [21].

3. IMAGE SEGMENTATION

Our approach for the segmentation of psoriasis images is based on the classification in a feature space constituted by the estimated local fractal dimension. We use a sliding analysis window in order to locally estimate the color fractal dimension. The obtained results are grouped in an intermediate pseudo-image of local color fractal dimensions which represents a ”multi-fractality map”. This image can be further processed (histogram thresholding, watershed, graph-cuts) in order to obtain the final segmentation map. The use of fractal features for skin characterization is sustained by the fact that the skin has approximately the same aspect at different zoom scales: micro and macroscopic.

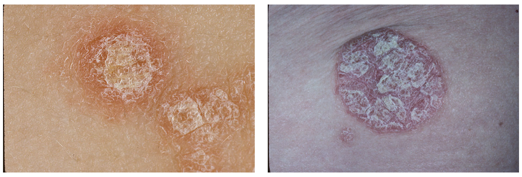
The sliding window size is one of the parameters of our approach. Given the nature of the box-counting algorithm i.e. computing a sliding window in another sliding window, its analysis window should be of an adequate dimension, depending on the size of the objects in the image. The used distance for determining how many pixels fall into a box is another parameter. Given its definition in RGB, a colour space which exhibits a cubical representation, the Minkowski norm is a good choice for a distance. The implications of choosing another colour distance, with respect to the theoretical Hausdorff dimension, have to be studied and verified.

The number of boxes used is a specific parameter for the box-counting algorithm. In theory, this number has to be as large as possible, so the fractal hypothesis could be verified on at least two decades in the log-log space [22]. However, due to the discrete nature of the image and due to the sliding window size the number of boxes is limited. For the same analysis window, an increased number of boxes will allow a larger range of values for the fractal dimension and thus moving the histogram towards the higher values.

4. EXPERIMENTAL RESULTS

Our work is based on the assumption that the regions representing the skin lesions have a different fractal dimension than the rest of the image representing the healthy skin. If we use a sliding window and locally compute the fractal dimension, the resulted values computed on uniform regions will be smaller than the values computed on regions containing edges or high complexity texture zones.

If the algorithm is applied on a uniform color image, the resulted fractal dimension is 2.0, indicating that the image complexity is zero. For a healthy skin image, the fractal dimension is usually less than 3.0, which is the maximum complexity of a grey-scale image, depending on the complexity of the skin texture. This result is close to a highly complex surface in the grey-scale domain. However, the images containing psoriatic lesions (Figure 1) have a considerable spread of information in the color domain, therefore their fractal dimensions should be greater than 3.0.



(a) psoriatic lesion 1 (b) psoriatic lesion 2

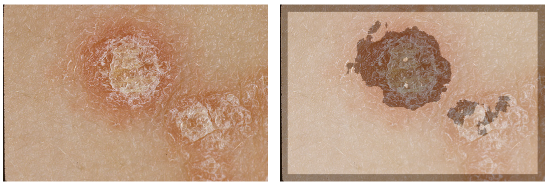
Figure 1*: Example of psoriatic lesion images.*

Before presenting our experimental results, we present and discuss the results given by the most-used segmentation approaches (Canny edge detection, JSEG, Pyramidal decomposition, watershed), usually available in widely-used libraries available in Matlab or OpenCV. Because of the highly-complex colour texture of the psoriatic lesions, most of the segmentation techniques give unsatisfying results, as one can see in Figure 2. Based on our results, we conclude that a feature-based segmentation approach is more appropriate, capable of characterizing the colour texture in a multi-scale manner, like the fractal measures do.

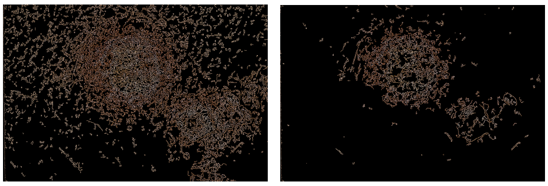
The most used and refined technique of contour (edge) detection is the algorithm proposed by Canny. However, an image containing psoriatic lesions has too many edges due to the complex surface of the damaged skin. Therefore the Canny algorithm fails in finding the desired regions of segmentation (Figure 2(c) and Figure 2(d)) from the medical application perspective.

In the case of region-based segmentation techniques, the most used are JSEG, watershed and pyramidal decomposition. Deng's JSEG algorithm is based on a quantization performed only in the color space alone without considering the spatial distributions. Depending on a threshold chosen by the user, the resulted regions are merged together. In Figures 2(e) and 2(f) two segmentation of the psoriatic lesions are presented. The threshold for colour quantization was the default in the available implementation of JSEG, while the region merging thresholds were 0.1 and 0.4.

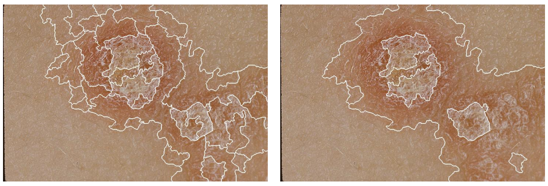
In the pyramid segmentation algorithm, instead of performing image segmentation based on a single representation of the image, the image components are described using multiple representations with decreased resolutions. However, in our case of psoriatic lesions, the low resolution representations of the image lose their initial texture characteristics. In addition, the algorithm we used (available in the OpenCV library) is also parametrical so the user can select the number of levels used and two error thresholds. In Figures 2(g) and 2(h) is presented a result for the segmentation of our initial image using this method.



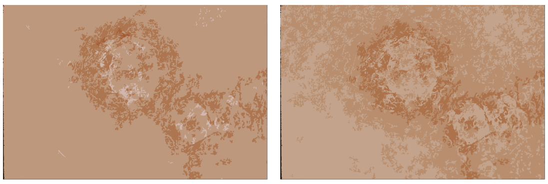
(a) test image (b) our approach



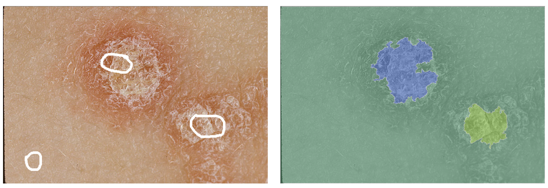
(c) Canny, $th = 50$ (d) Canny, $th = 100$



(e) JSEG, $th = 0.1$ (f) JSEG, $th = 0.4$



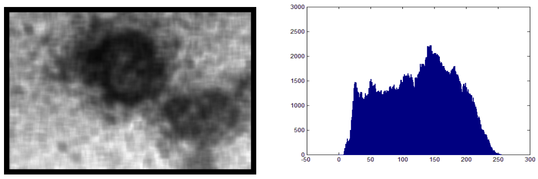
(g) pyramidal decomposition, $th_1 = 255$, $th_2 = 35$ (h) pyramidal decomposition, $th_1 = 70$, $th_2 = 35$



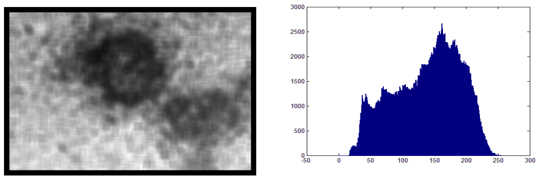
(i) watershed markers (j) watershed segmentation

Figure 2: *Example of a psoriatic lesion image and several possible segmentations.*

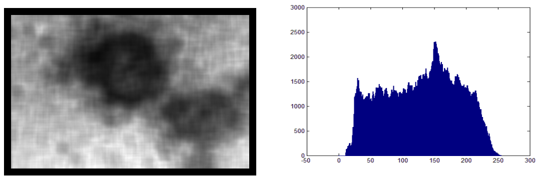
In the watershed algorithm the image is seen as a topographic relief where the luminance of a pixel represents its altitude in the relief. The relief is then flooded started from a previous defined set of markers. The drawback of this algorithm is the fact that the user has to choose the initial markers, for a generic application. However, this could not be considered an issue from the point of view of a medical application, when the specialist may manually place the markers. In Figure 2(j) is presented a resulted image segmentation starting from the initial markers in Figure 2(i).



(a) window size: 31; 7 boxes (b) histogram of Figure 3(a)



(c) window size: 31; 9 boxes (d) histogram of Figure 3(c)



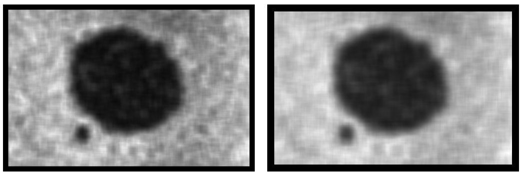
(e) window size: 41; 7 boxes (f) histogram of Figure 3(e)

Figure 3: *"Multi-fractality maps" of the image in Figure 2(a) (left column) and their histograms (right column).*

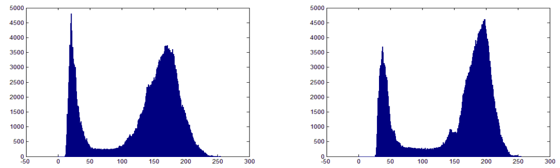
In Figure 2(b) we present the resulting feature map of our approach when the probabilistic box-counting algorithm was used to produce a "multi-fractality map". The histogram of the local fractal dimension was then thresholded by choosing the appropriate value for discriminating between the values of fractal dimension corresponding to the healthy skin and the values corresponding to the lesions. As a general remark, the results depend mainly on the size of the sliding window and the method chosen for the regression line. These parameters allow us to refine the segmentation map.

We applied the probabilistic box-counting algorithm on the test images and the results are presented in Figure 3. The analysis window size was 31×31 and 41×41 and the number of boxes was 3 and 4. As one can see, the algorithm generates local criteria pseudo-images in which the high complexity and the low complexity regions are represented through different levels of luminance, using a linear mapping. For the same analysis window, an increased number of boxes will allow a larger range of values for the fractal dimension and thus moving the histogram towards higher values (see the corresponding histograms in Figure 3). This fact allows us to improve the analysis by choosing a more accurate threshold. For different sliding window sizes the segmentation map becomes blurrier as the window size increases. Thus a smaller sliding window size is more accurate for the segmentation through thresholding.

In Figure 4 the results obtained by applying the algorithm on the image in Figure 1(b) are presented. In this case, from the shape of the generated maps histograms, it is clear that a histogram thresholding is suitable for segmentation of psoriatic images. However, we envisage combining the fractal local features with more elaborated segmentation techniques (like watershed).



(a) window size: 31; 7 boxes (b) window size: 41; 9 boxes



(c) histogram of Figure 4(a) (d) histogram of Figure 4(b)

Figure 4*: "Multi-fractality maps" of the image 1(b).*

5. CONCLUSION

In this paper we present a segmentation approach based on the estimation of the local color fractal dimension, computed using our colour extension of the Voss probabilistic approach. We discuss the parameters involved and their impact on the results. We applied this algorithm to skin images of psoriasis lesions, with both high and low complexity regions, and we compare our results with the results given by the most used segmentation techniques. The approach could be extended to other skin lesions like carcinoma or melanoma, but we haven't investigated yet the appropriateness of the fractal model for such lesions.

We applied the algorithm only on a reduced set of images, but we are in the process of creating our own image database for psoriasis, given that there are only very few existing databases, which are not fully available and which are not properly constructed - the acquisition conditions are not specified, especially the information about the illuminant or the zoom factor.

Given the particular highly-complex colour texture of the psoriasis images, which exhibits a large variation both in the chromacity and in the spatial organization, the most appropriate segmentation technique should take into account all the aspects of the complexity of the colour texture. The existing segmentation approaches, except for JSEG, are based only on colour distances, regardless the topology of the psoriatic colour texture, being thus unable to properly segment the images. Our approach has two major advantages: it is a fully colour approach (without any colour quantization or any marginal analysis of the independent components) and a multi-scale texture analysis by definition. However, the results show that the segmentation phase of our approach has to be refined by using a watershed or a graph-cuts technique, based on the colour fractal criteria used. Even if the segmentation seems to be correct from a medical point of view, we envisage using and proposing objective quality metrics to assess the performance of our approach.

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