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Multi-fractal Techniques for Emphysema Classification in Lung Tissue Images

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Abstract. This paper presents a multi-fractal based approach for the classification of emphysema patterns by calculating the local singularity coefficients of an image using different intensity measures. One of the primary statistical measures of self-similarity used in the processing of tissue images is holder exponent (α-value) that represents the power law which the intensity distribution satisfies in local pixel neighbourhoods. The fractal dimension corresponding to each α-value gives a multi-fractal spectrum f(α) that could be used as a feature descriptor for classification. Experimental results show that multi-fractal spectrum could be effectively used for the classification of histopathological cases. Some important implementation aspects of the multi-fractal based classification scheme that could be used for improving classification accuracy are also discussed.

Keywords: emphysema classification, multi-fractal analysis, multi-fractal spectrum, histogram comparison, statistical self-similarity.

1. Introduction

Emphysema is one of the main components of chronic obstructive pulmonary diseases (COPD); it is characterized by loss of lung tissue and may eventually leads to gradual destruction of the lung. Detection and classification of emphysema is therefore very important as this may lead to improved computer aided diagnosis (CAD). Diagnosing emphysema usually requires pulmonary function tests (PFTs), combined with a history of symptoms. The main tool through which the tests are performed is the spirometer; however, PFTs are not capable of detecting COPD at early stages. Another popular tool for diagnosing emphysema is high resolution computed tomography (HRCT) imaging. CT imaging is a suitable method for demonstrating the presence, distribution and extent of emphysema patterns in images. Emphysema in HRCT is characterised by the presence of areas of abnormally low attenuation which can be easily contrasted with surrounding normal lung parenchyma [1]. Emphysema can be classified into three different classes: centrilobular emphysema (CLE), paraseptal emphysema (PSE) and panlobular emphysema (PLE) [1], [2] has recently introduced new methods for texture analysis in CT images using local binary patterns (LBP) that achieved promising results in the classification of emphysema subtypes.

The intensity distribution in lung tissue images is highly irregular and does not often permit a direct definition of shape parameters using geometrical descriptors. One approach towards extracting relevant features is to make use of the statistical self-similarities in local intensity variations. Most biomedical images exhibit such statistical self-similarity, a repetition of form over a variety of scales. Several methods of multi-fractal analysis of medical images have been suggested and evaluated in different ways [3]-[16]. Hemsley and Mukundan [3] developed two-pass algorithm for the computation of multi-fractal spectrum and used the calculated spectra for the classification in a tissue image database. In [4], the holder exponent for the power

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law approximation of intensity measures in pixel neighbourhoods is used for resolving local density variations in the CT lung images.

This paper proposes a novel algorithm for emphysema classification based on multi-fractal spectra computed from the images. The remainder of this paper is organized as follows: In section 2, different intensity measures used for the computation of Holder exponent and the overview of the multi-fractal methods are outlined. Experimental results and discussion are given in section 3. Section 4 discusses the details of the implementation aspects that are useful for the experiments. Finally, section 5 summarizes the work and outlines some future directions.

2. Material and Methods

The online CT emphysema database [5] used for this research consists of 168 non-overlapping annotated ROIs of size 61×61 pixel patches from three different classes: NT (59 never-smokers), CLE (50 healthy smokers), and PSE (59 smokers with COPD) [14]. The system overview for the multi-fractal approach of emphysema classification is shown in Figure 1. The process involves several algorithmic stages, first of which is the calculation of the holder exponent (α-values) at each pixel using a pre-selected intensity measure defined in pixel neighbourhoods. This computation is explained in detail in Section 2.1. The α-values describe the variation in local density of the image with respect to the chosen measure. The collection of all α-values for a given image is referred to as the α-image. The range of α-values is subdivided into a number of small intervals, effectively decomposing the α-image into several disjoint image slices. Each α-image slice represents the collection of pixels in the input image having similar intensity variation (obeying similar power-law relationship in the intensity measure) across pixel neighbourhoods. The traditional box-counting method is used for the calculation of the fractal dimension f (α) of the α-images, providing the multi-fractal spectrum. The pixels having similar α-values collectively yield a α-histogram. Both the α-histogram and the multi-fractal spectrum contain highly discriminative texture features. Such features are gathered to form a descriptor and used in the image classifier.

2.1. Holder exponent and multi-fractal measures

Multi-fractal analysis describes the fractal properties of an image using an intensity-based measure within the neighbourhood of each pixel. The local singularity coefficient, also known as the Holder exponent [7]-[16], reveals the local behaviour of a measure function denoted as $\mu_p(w)$, where w stands for the window size centred at the pixel p. The variation of the intensity measure with respect to w can be characterised as follows:

$$\mu_p(w) = Cw^{\alpha_p}, \qquad w = 2k + 1, \quad k = 0,1,2,\ldots,m \tag{1}$$

where C is an arbitrary constant, and m is the total number of boxes used in the computation of α_p. The value of α_p can be estimated from the slope of the linear regression line in a log-log plot where log ($\mu_p(w)$) is plotted against log(w). Some commonly used multi-fractal intensity measures used for the computation of the holder exponent are outlined below.

The sum measure $\mu_p^{[sum]}(w)$ is defined as the sum of the intensity values within a local neighbourhood w. The measure could be further normalized using the total mass intensity to prevent values from becoming exceedingly large [10-11]. The iso measure $\mu_p^{[iso]}(w)$ counts the number of pixels that have the same intensity value with the centred pixel p in a neighbourhood. If the centred pixel is the only pixel with unique intensity in the region, then measure has a value 1. The inverse-minimum measure is $\mu_p^{[\min]}(w)$, which is defined as $1 - min_{q\in w}\, I_q$. Here, the intensity values I_q are assumed to be normalized in the range [1], so that the value resulting from subtraction is always positive. The subtraction from 1 is used to meet the requirement that the measure does not decrease in value with increasing window size. The maximum measure $\mu_p^{[\max]}(w)$ is the measure with the greatest intensity value found in the window w centered at the pixel p.

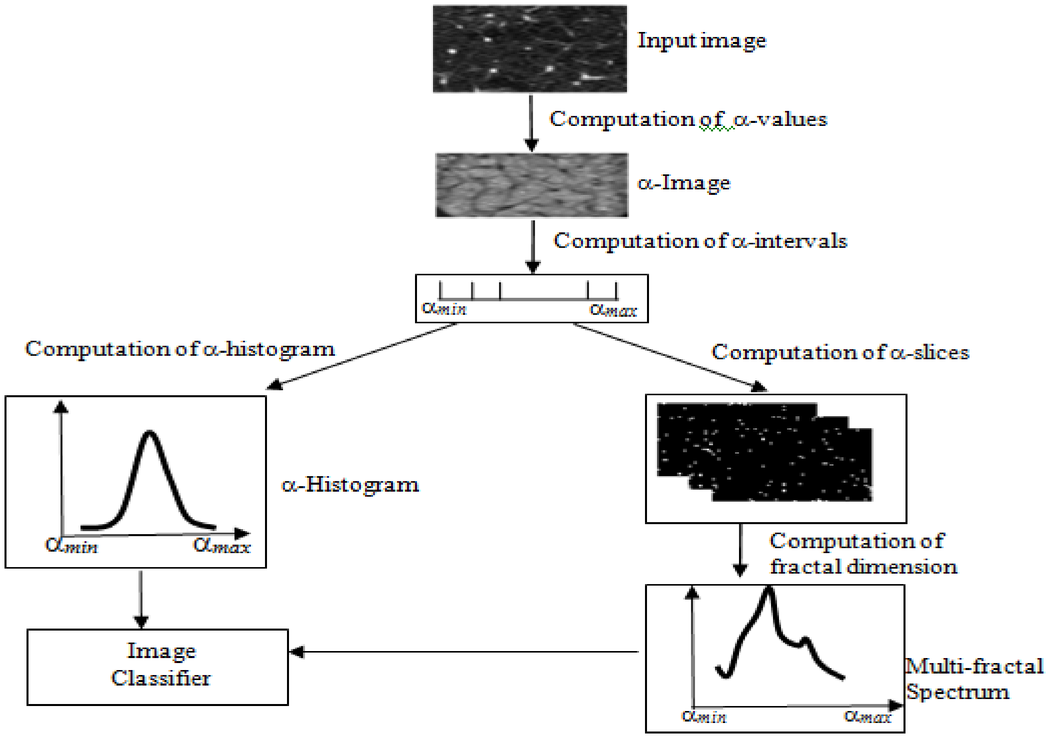


Fig. 1: System overview of multi-fractal based classification of CT emphysema

2.2. α-Images and the multi-fractal spectrum

The α_p values at pixels p obtained from the previous step define a range $[\alpha_{min}, \alpha_{max}]$ of the real line, which is further divided into n discrete steps $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_n$. Each intermediate value α_k is defined as follows:

$$\alpha_k = \alpha_{min} + (k-1)\,\Delta\alpha_k, \qquad k = 1,2,\ldots,n, \qquad \Delta\,\alpha_k = (\alpha_{max} - \alpha_{min})/n. \tag{2}$$

For our experimental analysis, we used the value $n = 100$. An important texture feature that could be used in classification is the statistical self-similarity property exhibited by the sub-images represented by the α-slices. Each α-slice can be characterised by its fractal dimension $f(\alpha_k)$. This fractal dimension is computed using the well-known box-counting algorithm [9]. The variation of $f(\alpha_k)$ with α_k, $k = 1,2,\ldots n-1$ gives the multi-fractal spectrum.

3. Experimental Results and Discussion

In this section, we outline experimental results obtained using images from the emphysema database [5], based on the implementation of methods discussed in the previous section. The classifier used the features derived from averaged multi-fractal spectra of four randomly selected images belonging to each class as the training samples and the features from the calculated multi-fractal spectra of 16 images from each class as the test samples. The results of the multi-fractal descriptors obtained for the three classes of the emphysema images using four multi-fractal intensity measures (Section 2.1) are presented in Figure 2. The three distance metrics used for the experiments include; the Manhattan, the Chi-square and the Bhattacharyya distance [8].

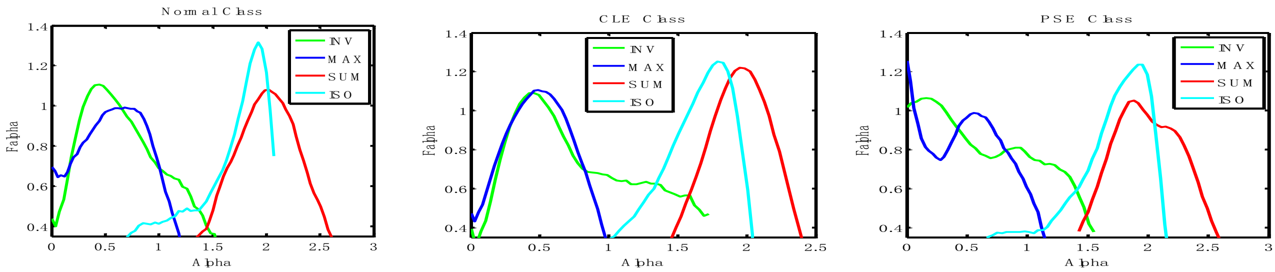


Fig. 2: Multi-fractal descriptors for three classes of emphysema images using each intensity measure, after each spectrum is smoothed with the moving average algorithm.

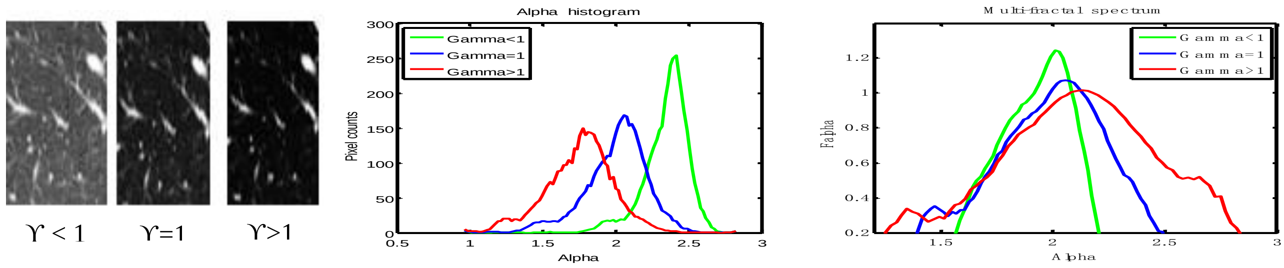
The classification is done with a K-nearest neighbour (KNN) classifier using the three distance metrics to measure the similarity between the images. The classification results in a form of confusion matrices using the selected measures are given in Table 1. The proposed approach performs well in terms of separating the normal lung CT tissues from the pathological cases using the sum intensity measures. The results obtained by the inverse minimum and iso measure are also acceptable but contain some classification errors. However, the results generated for assessing the severity of emphysema in CT images using the multi-fractal approach are not good enough. Overall, the Bhattacharyya distance using all the intensity measures performs worse than other distance metrics while Manhattan distance gave the best overall classification results.

Table 1: Comparison of classification results using different distance metrics and LBP

		Predicted											
		Bhattacharya			Chi-Square			Manhattan			LBP		
		NT	CL	PS	NT	CL	PS	NT	CL	PS	NT	CLE	PSE
Actual	NT	100	0	0	100	0	0	100	0	0	93	0	7
	CL	58	42	0	41	59	0	50	50	0	2	98	0
	PS	17	42	41	17	25	58	17	25	58	3	2	95

The multi-fractal based classification results obtained (Table 1) are compared with the recently published LBP results. The LBP result used for comparison (Table 1) is taken from the joint LBP and intensity histograms approach reported by [14]. The confusion matrices generated by the intensity measures clearly show that the LBP result slightly performs better than our results. Although, the sum measure performs better than the LBP results for the separation of normal tissues but gives more errors in CLE and PSE classes. Our method is simpler and the results we have achieved looks very promising.

There are a number of ways by which the accuracy of the results could be improved, such as reducing the total number of boxes used for the computation of α, deleting the α-values represented with few pixels in the image and selecting the appropriate number of α sub-intervals [10]. Additionally, we could also map the intensity limits of the α-image automatically into a new range by using the contrast stretching. However, the contrast adjustment may be non-linear, which may affect the accuracy of the multi-fractal spectrum. We therefore introduced a gamma correction factor to map the α-image's intensity from low and high to values between bottom and top. The α-histograms and the corresponding multi-fractal spectra of the normal emphysema image demonstrating the effect of gamma factor are presented in Figure 3. When Gamma is 1, the mapping is linear and does not affect the α-histogram and the multi-fractal spectra but when Gamma is less than 1, the α-histogram shifted towards higher values of α, which slightly brightens the corresponding image. Also, when Gamma is greater than 1, the α-histogram shifted towards the leftward position, causing the greater number of pixels to have lower α values and hence darkens the output image.



(a) (b)

Fig. 3: Effect of image intensity adjustment using gamma correction factor on α-histogram and multi-fractal spectra, and the corresponding output images. (a) Transformed images (b) Comparison of α-histogram and multi-fractal spectrum

4. Conclusion and Further Work

This paper has presented a multi-fractal based approach for emphysema classification in pulmonary CT images using the features derived from multi-fractal descriptors. The multi-fractal spectrum of the emphysema images has been computed using four different intensity measures; the summation, iso-surface, maximum and inverse minimum measures. The classification results obtained in the form of confusion matrices demonstrated that multi-fractal can be used as a global descriptor. The proposed approach using the sum intensity measure perfectly separated the normal lung tissues (NT) from other pathological cases (CLE and PSE). Comparative analysis using three different distance measures are also discussed, and the effect of each measure in the classification results are investigated. This research could be further improved by combining the features from the alpha-histograms and the multi-fractal features to design a new method with better discriminative power for assessing the severity of emphysema in CT images. Increasing the number of feature vectors of the multi-fractal descriptors for the classification process could also increase the classification accuracy.

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