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CHARACTERIZATION OF STROKE LESION USING FRACTAL ANALYSIS

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ABSTRACT

Objective: The characterization of stroke lesions is a challenging research issue due to the wide variability in the structure of lesion patterns. The objective of this research work is to characterize the stroke lesion structures using fractal analysis.

Methods: To characterize the complex nature of the lesion structures, fractal box counting analysis is presented in this work. Three parameters from fractal dimension (FD) are considered to characterize the nature of the normal and abnormal brain tissues.

Results: The experimental results are presented for 15 different datasets. Three different parameters namely FD average, FD deviation, and FD lacunarity are extracted to quantify the properties of the stroke lesion. The observations indicate that there is a significant proportion of separation of feature values between the normal and abnormal brain tissues.

Conclusion: This work presents an efficient scheme for characterizing the stroke lesions using fractal parameters. It could be further enhanced by incorporating features extracted from other non-linear techniques.

Keywords: Lesion, Multifractal analysis, Magnetic resonance imaging.

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INTRODUCTION

Stroke is one of the significant reasons behind death after cancer and cardiovascular disorders. Computed tomography (CT) and magnetic resonance imaging (MRI) modalities play a crucial role in the assessment of patients affected by stroke. These modalities capture the presence of stroke lesion in different ways depending on the modality. Many research works were presented for characterizing such lesions in the last two decades [1-4].

Grzesik *et al*. presented a histogram-based characterization study for describing the properties of stroke lesion from multimodal MRI images [1]. Schaefer *et al*. presented a characterization study for the evolution of stroke lesion [5]. Rajini and Bhavani presented a detection scheme for ischemic stroke using gray level co-occurrence matrix features and support vector machines [6]. Tang *et al*. presented a similar scheme using a circular window [7].

Thangavel *et al*. introduced a method to predict the carotid plaque lesions using Contourlet transform [8]. Sajjadi *et al*. introduced a novel approach on CT images to identify the early indicators of stroke utilizing wavelet features [9]. Most of the characterization studies discussed were focused either in spatial or frequency domain techniques.

Non-linear techniques can characterize the biological systems in an efficient way [10]. Out of the different non-linear techniques, fractal-based features were examined well for different medical signal processing works. This research aims at exploring the strength of fractal-based features for characterizing the properties of stroke lesions.

Background review

The brief discussion of the techniques associated with the proposed work is discussed in this section.

Fractal analysis

Fractal is a non-uniform geometric structure which resembles the same construction of shapes at all ranges [11]. Fractal dimension (FD) can be used to quantify the texture of the fractal, and it is a non-integer quantity. fractional Brownian motion (fBm) could be applied to quantify the texture properties of the image. The fBm process could be described as continuous-time Gaussian process "$F_H(t)$" with zero mean. The covariance structure is as follows,

$$E\left[F_H(t)F_H(s)\right]=\frac{1}{2}\left(|t|^{2H}+|s|^{2H}-|t-s|^{2H}\right) \quad (1)$$

Where, H is Hurst index and it is a scalar parameter varies between 0 and 1. The fBm process is determined by the H value. If H=0.01 the curve $F_H(t)$ is very rough while the curve is smooth for H=0.99.

The relation between Hurst coefficient and FD is as follows,

$$FD = E + 1 - H \quad (2)$$

Where, E is the Euclidean dimension.

METHODS

The proposed scheme initially applies watershed transform-based segmentation procedure was to isolate the region of interest. Then, the box-counting-based fractal analysis is carried out to determine the FD. Three parameters namely FD average, FD deviation, and FD lacunarity were extracted to describe the properties of the stroke lesion. The architecture of the proposed approach was presented in Fig. 1.

Image acquisition

The MRI datasets were acquired from different online and offline sources. Out of the 15 datasets, 8 datasets are abnormal due to ischemic stroke and the remaining sets are normal. The imaging format of the MRI slices was in the Digital Imaging and Communication in Medicine.

Segmentation

This work applies watershed transform for segmenting the lesion boundaries from the input images. It basically considers the intensity pixel values as the height of the water basin. The water drops gradually slide along the maxima of intensities to finally reach the local minima. As a result, the watershed generated is analogous to the boundary of the segmented regions.

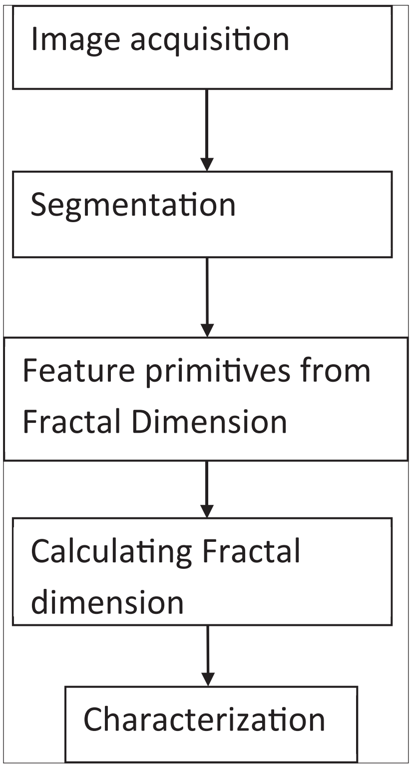


Fig. 1: Proposed approach

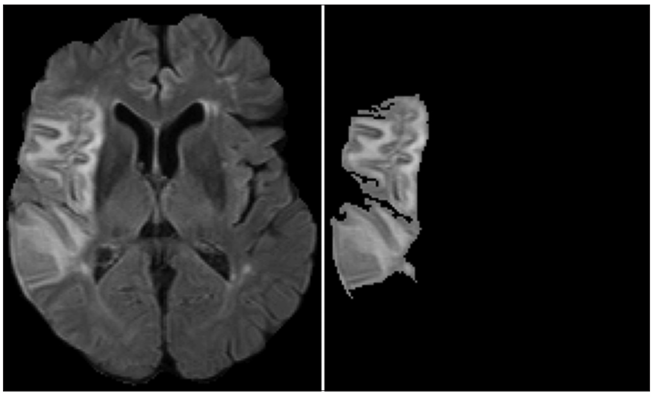


Fig. 2: Segmented results for abnormal images

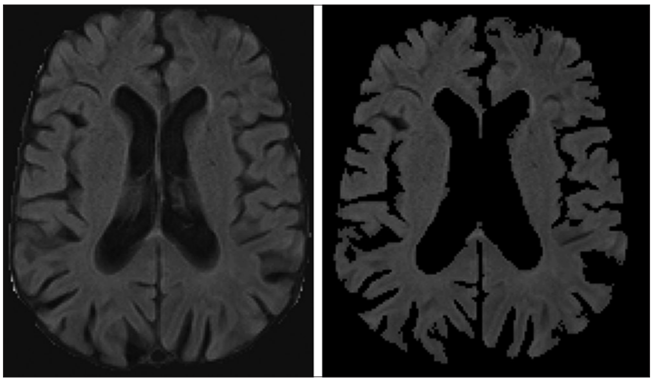


Fig. 3: Segmented results for normal images

Figs. 2 and 3 presents the segmented regions obtained after applying watershed-based process to the input images. It can be observed that the portion corresponding to lesions are identified as local maxima in the input images. Similarly, for the normal brain tissues, the white matter content was dominantly detected.

Fractal dimension

In this work, the box-counting-based approach is applied to determine the FD. Box-counting is a technique of breaking a structure into tiny pieces, typically box-shaped, and accumulating data to examine the pieces at smaller scales. The importance of the technique is to observe the changes in the details of the image with respect to scale changes.

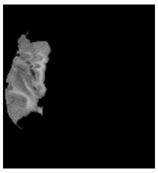
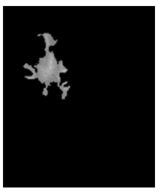
Feature extraction

Three parameters namely FD average, FD deviation, and FD lacunarity were extracted to describe the properties of the stroke lesion. The parameter FD average provides the average FD values by determining the FDs with different holder exponent values. The parameter FD deviation presents the distribution of the fractal variation of an object. The parameter FD lacunarity will quantify how well the generated patterns fill the space. These parameters are calculated for different images, and the resultant observations are tabulated in Tables 1 and 2.

RESULTS AND DISCUSSION

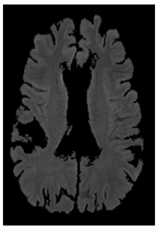
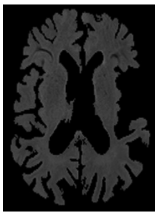
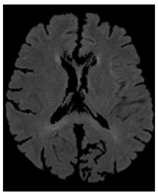
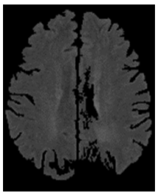
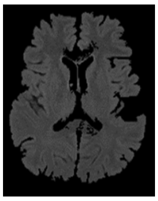
The software platform using for implementing this work is MATLAB 2015. The system configurations are 6 GB RAM and 500 GB hard disk capacity. Three parameters namely FD average, FD deviation, and FD lacunarity were extracted to describe the properties of the stroke

Table 1: Parameters obtained for lesion

Images	FD average	FD deviation	FD lacunarity
	1.2865	0.6761	0.1994
	1.1777	0.6745	0.2042
	1.1135	0.7002	0.2196
	1.2522	0.7829	0.2939
	0.9284	0.7716	0.2873

FD: Fractal dimension

Table 2: Parameters obtained for normal images

Images	FD average	FD deviation	FD lacunarity
	1.514	0.7867	0.3739
	1.4928	0.8752	0.5522
	1.4941	0.8717	0.6127
	1.4442	0.7915	0.3995
	1.4395	0.9736	1.0994

FD: Fractal dimension

Table 3: Feature statistics for lesion

Sample	FD average	FD deviation	FD lacunarity
1	1.2865	0.7867	0.3739
2	1.1777	0.8752	0.5522
3	1.1135	0.8717	0.6127
4	1.2522	0.7915	0.3995
5	0.9284	0.9736	1.0994
6	1.2037	0.8368	0.4832
7	1.2311	0.8085	0.4313
8	1.2554	0.752	0.3588
9	1.263	0.7521	0.3545
10	1.3152	0.691	0.276
11	1.3467	0.716	0.2827
12	1.211	0.8263	0.4655
13	1.3074	0.7371	0.3178
14	1.2278	0.8148	0.4404
15	1.2687	0.7844	0.3822
16	1.2764	0.7724	0.3662
17	1.356	0.7976	0.3459
18	1.3588	0.7808	0.3301
19	1.3355	0.7901	0.35
20	1.3472	0.7749	0.3308

FD: Fractal dimension

lesion. The observations obtained for these parameters for 20 different samples are presented in Tables 3 and 4.

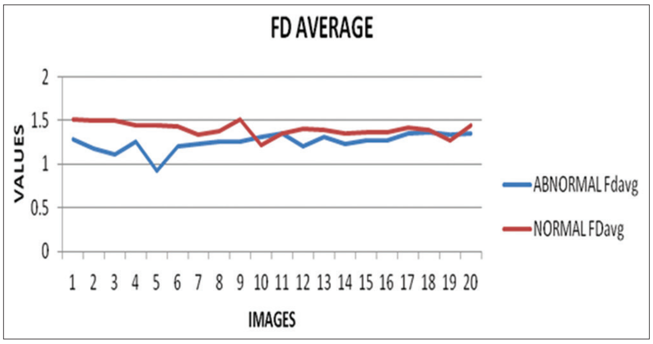


Fig. 4: Fractal dimension average values for abnormal and normal images

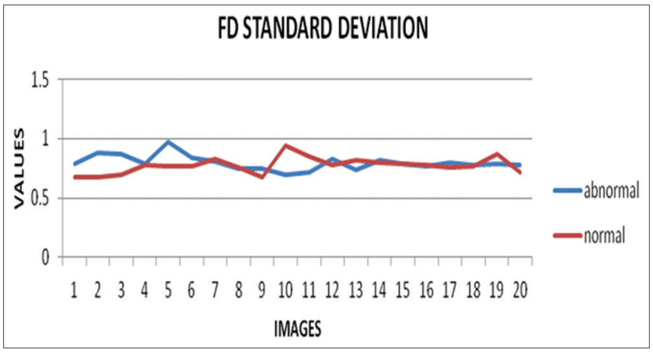


Fig. 5: Fractal dimension standard deviation values for abnormal and normal images

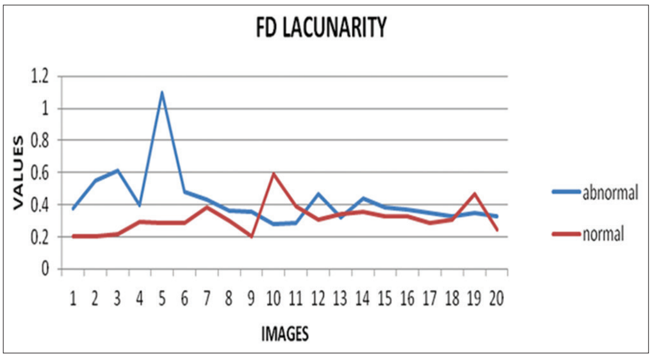


Fig. 6: Fractal dimension lacunarity values for abnormal and normal images

From Fig. 4, it is observed that the results obtained from FD average for abnormal images are in the range between 0.9284 and 1.3588 and for normal images, it is in the range between 1.2247 and 1.5154. By observing the ranges of normal and abnormal images, it is showing that the abnormal images having low range compared to normal images.

From Fig. 5, presents the observations obtained for FD deviation parameter. It is observed that the results obtained from FD standard deviation for abnormal images are in the range between 0.691 and 0.9736 and for normal images, it is in the range between 0.6745 and 0.9434.

From Fig. 6, it is observed that the results obtained from FD lacunarity for abnormal images are in the range between 0.276 and 1.0994 and for normal images, it is in the range between 0.1994 and 0.5896. By observing the ranges of normal and abnormal images, it is showing that the abnormal images having high range compared to normal images.

Table 4: Feature statistics for normal brain tissues

Sample	FD average	FD deviation	FD lacunarity
1	1.514	0.6761	0.1994
2	1.4928	0.6745	0.2042
3	1.4941	0.7002	0.2196
4	1.4442	0.7829	0.2939
5	1.4395	0.7716	0.2873
6	1.4297	0.764	0.2856
7	1.3372	0.8263	0.3818
8	1.3831	0.7601	0.302
9	1.5154	0.6767	0.1994
10	1.2247	0.9404	0.5896
11	1.3553	0.8452	0.3889
12	1.3996	0.7772	0.3084
13	1.3944	0.8173	0.3436
14	1.3489	0.8026	0.354
15	1.3696	0.7861	0.3294
16	1.3654	0.7777	0.3244
17	1.4189	0.7582	0.2855
18	1.3967	0.7697	0.3037
19	1.2719	0.8683	0.466
20	1.4513	0.7148	0.2426

FD: Fractal dimension

CONCLUSION

A characterization scheme for stroke lesion using FDs is presented in this work. Three different parameters namely FD average, FD deviation, and FD lacunarity are extracted to quantify the properties of the stroke lesion. There is an overlap between the ranges of the values obtained for all the parameters for few samples. Hence, the future work will be oriented toward exploring advanced techniques with fractal analysis.

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