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Multifractal Analysis for Detection of Angiography Image

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Abstract- A new texture descriptor is proposed to classify texture based angiography images. The input image is preprocessed using the anisotropic diffusion. The preprocessed image is normalized to improve the robustness of the wavelet co-efficient to scale changes. The wavelet co-efficient are used to encode both low frequency and high frequency information of images in a multi scale manner. However some statistical measurements on wavelet co-efficient such as negative moments can be unstable since a significant percentage of wavelet coefficients of natural images tend to be small. Thus, in addition to wavelet co-efficient, a modified version of the so called wavelet leader's technique is included as one dimensional measurement of texture images. So multi-fractal spectrum features can be used since it incorporates both negative and positive moments. Features are extracted from the MFS and fed into the ELM classifier to classify the images as normal or abnormal images.

Index – Anisotropic diffusion, ELM classifier, Fractal dimension.

I. INTRODUCTION

In image processing classification constitutes a standard task that can be based on image texture analysis. Angiography is medical imaging technique used to visualize the inside of blood vessels and organs of the body, with particular interest in the arteries, veins and the heart chambers. There is many problems in the angiography which are Coronary angiography, Micro angiography, Neuro-vascular angiography, and Peripheral angiography. These are all visualizing the blood vessels. Microangiography is commonly used to visualize tiny blood vessels. One of the most common angiograms performed is to visualize the blood in the coronary arteries.

In the existing texture analysis the WMFS texture descriptor is based on the statistical measure on the distribution of different types of pixels. Thus, it also suffers from the often seen weakness as many other statistical methods, that is, it requires sufficient pixels to have an accurate and stable estimation. As a result, the WMFS does not [1] work very well on the static texture images of very low resolution method. However, such a weakness is not severe for DT recognition.

In the proposed texture analysis a image texture descriptor that combines wavelet-based representation and multi-fractal analysis to gain both strong descriptive power and robustness against environmental changes. In the proposed approach, we first preprocess the image using anisotropic diffusion technique. The selected preprocessed image is normalized to improve the robustness of the scale changes. The normalized image is applied to multi orientation wavelet and wavelet leader to avoid sensitivity problem of wavelet transform. Then, instead of directly using these measurements, we apply multi-fractal spectrum (MFS) analysis on these wavelet coefficients to extract robust texture descriptors. The standard deviation and tamura features are extracted from the MFS and fed into the ELM classifier to classify the images as normal and abnormal images. Experimental evaluations on fifty normal and abnormal images are performed and also we can calculate the sensitivity, specificity and accuracy of the system.

II. RELATED WORKS AND OUR APPROACH

In this section, we only summarize recent studies that are most revelant to our work

1) Scale Normalization:

Scale normalization aims to improving the robustness of the wavelet coefficients to scale changes. we propose to use scale-normalized texture images as the input for wavelet transform. The estimate of the texture scales is derived from the statistics of scale invariant patches. In this implementation, the Laplacian blob detector is used to collect scales of local patches[2,5], followed by a global scale estimation of the whole textured image.

Specifically, for an input texture image I , we first use the local patch detector to extract local elliptic patches and keep the T largest patches, denoted as $\{\mathbf{p}1, \mathbf{p}2, . . . , \mathbf{p}T\}$. Then scale t of the image is estimated as

$$t = \sqrt{1/T \sum_{i=1..T} \text{area}(\mathbf{p}i)}. \text{---- (1)}$$

where T is the fixed value which is used to estimate the scale t. Finally the normalized image is generated by scaling the image I by the factor t0/t.

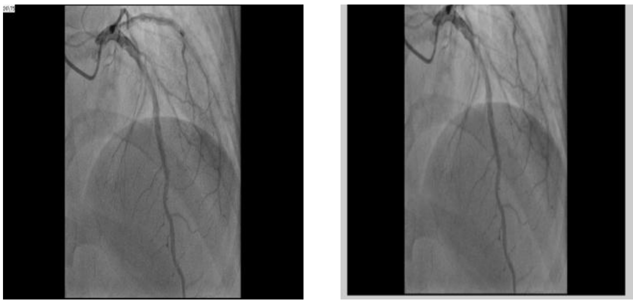
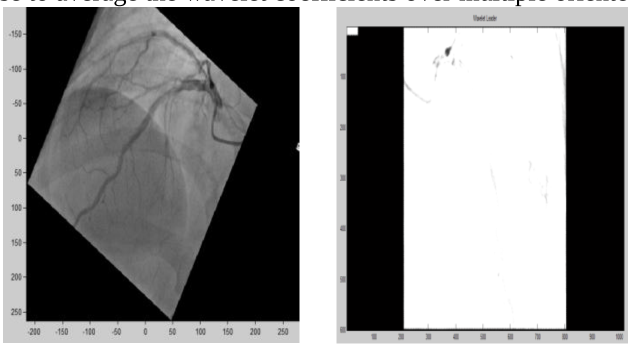


Fig 1 (a) Angiography Image (b) Scale normalized image

2) Multi-Orientation Wavelet and Wavelet Leaders:

Wavelet coefficients are known to encode both low-frequency and high frequency information of textures in a multi-scale manner. However, some statistical measurements on wavelet coefficients, such as negative moments, can be unstable since a significant percentage of wavelet coefficients of natural images tend to be small. Thus, in addition to traditional wavelet coefficients, a modified version of the so-called wavelet leaders technique [1] is included as one additional measurement of texture images. The purpose is for facilitating the robust computation of multi-fractal spectrum of textures that relies on both positive and negative moments. Moreover, to suppress the orientation sensitivity of wavelet transform, we propose to average the wavelet coefficients over multiple oriented instances of texture images.



(a) (b)

Fig 2(a) Multi orientation output (b) wavelet leader

In summary, the above multi-orientation wavelet and wavelet leader pyramids provide two complementary measurement sources that are stable for statistical computation and encode rich information regarding texture patterns.

3) Multi fractal Analysis:

Based on the above representation, a multi-fractal spectrum (MFS) is estimated for each individual wavelet domain, including the low-frequency domain, the high-frequency domain and the wavelet leader domain. The texture descriptor is then defined as the combination of the multi-fractal spectra estimated in all three domains(3). Here the fractal dimension is calculated using box counting method. The box-counting fractal dimension dim(P) is defined as

$$\dim(P) = \lim_{r\to 0} \log c(P, r)/-\log r \quad \text{--- (2)}$$

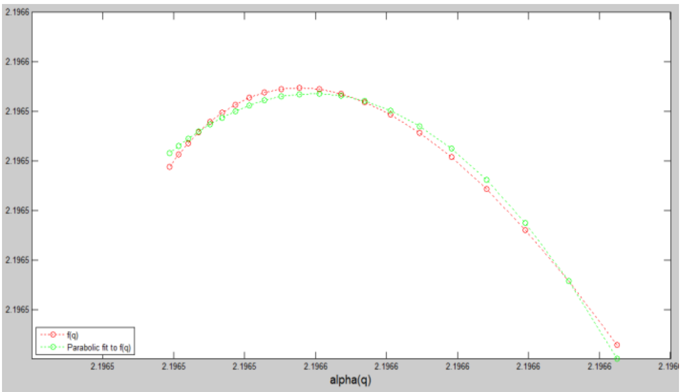


Fig 3.Multifractal spectrum

Multifractal analysis generalizes the fractal dimension to
characterize the irregularity of functions. Multifractal analysis divides the space into multiple point set $E\alpha$ according to some categorization term α.The MFS is then given by the multi-fractal function dim$(M\alpha)$ vs. α. In the classical definition of the MFS, the categorization term α is defined according to the "density "function, such as the image intensity[4].Then the MFS of X is calculated as

MFS$(X) = (\dim(M1), \dim(M2), \ldots, \dim(Md))$ - (3)

Our approach is not limited to the box-counting fractal dimension. The main reason we choose the box-counting fractal dimension is for its implementation simplicity and computational efficiency.

III. MULTI FRACTAL BASED IMAGE CLASSIFICATION

Our proposed image texture descriptor is built upon the multi fractal analysis in the wavelet pyramid domain. The standard deviation and tamura features are extracted from the multi fractal spectrum, which include both wavelet coefficients and wavelet leaders of multiple oriented instances of a given texture image. The proposed approach is

1) Anisotropic Diffusion Preprocessing:

In this proposed approach we use anisotropic diffusion is a preprocessing technique. Anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. This technique [4] resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process.

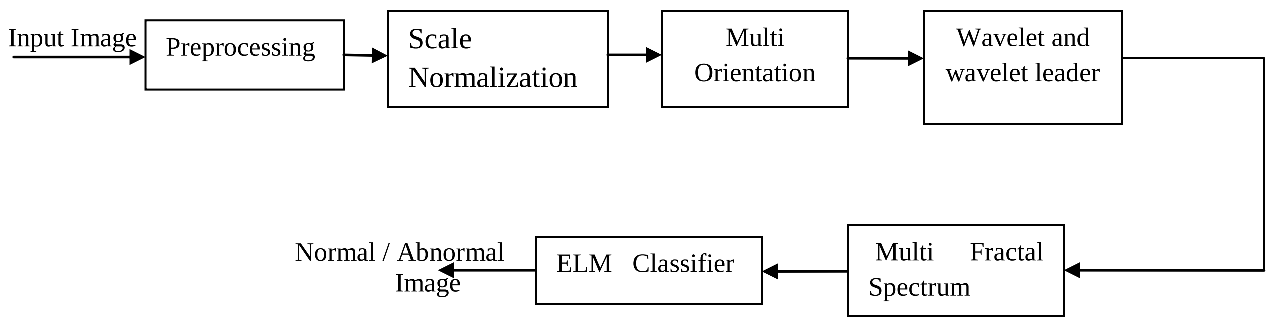


Fig 4. Over All Function Block Diagram

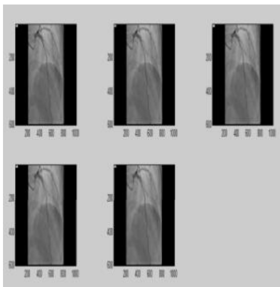


Fig.5.(a).Anisotropic diffusion for Normal image Fig.5.(b)Anisotropic diffusion for selected normal image

The anisotropic diffusion has five frame output from that we can retrieve the best image which has the clear information about the image.

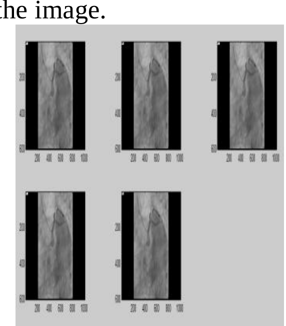


Fig.5.(a)Anisotropic diffusion for Abnormal image Fig.5.(b)Anisotropic diffusion for selected Abnormal image

2) Feature Set

The feature set includes standard deviation and tamura features. The anisotropic diffusion only operates on 2d gray scale images. we represent 3D color image into a sequence of 2D gray scale image. The standard deviation is represented by single feature value while tamura has five features and each have their single feature value. Tamura features are directionality, coarseness, roughness , irregularities, correlation. Tamura features are mainly used for texture images. These features which define the spatial arrangement of texture constituents help to single out desired texture types e.g. fine or course, close or loose. The features are extracted from the multi fractal spectrum of selected normal image.

Table 1: Feature Extraction

Tamura features					**Standard deviation**
F1	**F3**	**F4**	**F5**	**F6**	**SD**
0.6709	**0.7930**	**0.8730**	**0.8632**	**0.5928**	**0.8176**

3) Image Classification

For the classification process the ELM classifier is used to classify angiography image. It is multi class classifier which is a widely adopted algorithm in machine learning field is proposed for the use of image classification model using angiography images for identifying tissue abnormalities in heart. For the classification of angiography image anisotropic diffusion pixels are considered as samples. These samples are represented by a set of feature values extracted from different modalities. Features from all modalities are fused for image classification.. Since the features are extracted in 2D, each sample represents a pixel instead of a voxel. However the classification framework can readily be extended to 3D image[5]. The features are extracted from the MFS and fed into the ELM classifier to classify the images as normal and abnormal.

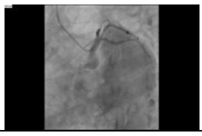
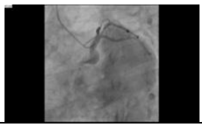
INPUT IMAGE	ELM OUTPUT	ELM TIME
	NORMAL IMAGE	0.221
	APNORMAL IMAGE	0.142
	APNORMAL IMAGE	0.1510

Fig 6: ELM Output and Time

4) Performance Evaluation

Receiver operating characteristic (ROC) curves are obtained to ascertain the sensitivity and specificity of the classifiers. The sensitivity, Accuracy, specificity, positive predictive value and Negative predictive value are calculated using the formulae 4 to 8 respectively. True Positive (TP) is the number of correctly classified pixels from the normal images, true negative (TN) is the number of correctly classified defective image in the normal image, false positive (FP) is the number of correctly classified image in the abnormal image and false negative (FN) is the number of correctly identified defective pixels in the abnormal image. These features parameters are computed as

$$Se = TP/(TP+FN) \quad (4)$$

$$Sp = TN/(TN+FP) \quad (5)$$

$$Ppv = TP/(TP+FP) \quad (6)$$

$$Npv = TN/(TN+FN) \quad (7)$$

$$Acc = (TP+TN)/(TP+FN+TN+FP) \quad (8)$$

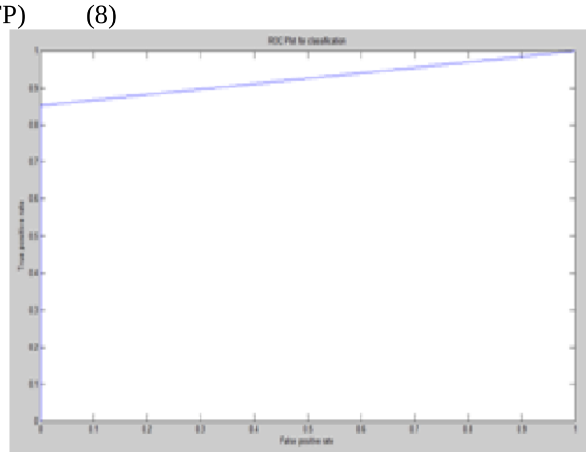


Fig.7. ROC for the classification. The x-axis denotes the false positive value and the y-axis denotes the true positive value.

The accuracy is 92.45% and the running time of ELM classifier is 0.1 seconds.

IV. CONCLUSION

A new texture descriptor is proposed to classify texture based angiography images. The combination of the scale normalization and multi orientation technique gi+,mves the high discriminative power and robustness to the classification of the image. It has several advantages which are 1) remove the sensitivity problem of wavelet transform 2) easy implementation. But the proposed approach suffers from the time complexity. The fractal dimension and wavelet leader consume more time to obtain the transformation. Because of the high time consumption the proposed approach have to analysis the optimization of time consumption.

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