COMPARISON OF WAVELET TRANSFORM, FRACTAL DIMENSION AND SECOND ORDER STATISTICS FOR TEXTURE ANALYSIS OF CAROTID ATHEROSCLEROTIC PLAQUES

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Abstract: Texture analysis of B-mode ultrasound images of carotid atheromatous plaque can be valuable for the accurate diagnosis of atherosclerosis. In this paper, three texture analysis methods, namely the wavelet transform, the fractal dimension and second order statistics, were used to characterize atheromatous plaques. B-mode ultrasound images of 10 symptomatic and 9 asymptomatic plaques were interrogated. A total of 87 texture features were estimated for each plaque. After dimensionality reduction using ANOVA statistics only four features were statistically different between the two investigated groups. These included two wavelet based texture features (standard deviation at scale 1 and horizontal detail image, standard deviation at scale 2 and horizontal detail image), the fractal dimension and one second order statistical feature (information measure of correlation). The fuzzy c-means algorithm was used to cluster texture features which were found statistically different between symptomatic and asymptomatic plaques. The combination of fractal dimension with information measure of correlation resulted in the highest classification performance (74%).

Introduction

The presence of an atheromatous lesion in the carotid artery is the largest single aetiological factor known to produce focal cerebral ischaemia, but in those with carotid bifurcation disease, only a minority have warning symptoms; the majority have their stroke from previously asymptomatic, also called stable, carotid lesions [1]. It has been shown that the instability of the carotid atheromatous plaque may be associated not only with the degree of stenosis but also with plaque echogenicity estimated from B-mode ultrasound images. B-mode ultrasound images offer valuable information about the composition of the atheromatous plaque, i.e., about the relative content of blood, lipids, fibrous tissue, and calcific deposits. Fibrous tissue and calcific deposits are echogenic materials, i.e. they reflect strongly the ultrasound signal, whereas blood and lipids are echolucent, i.e. they have less reflecting ability. This information is clinically important for a number of reasons. It has been shown that echolucent plaques, as evaluated by B-mode ultrasound, are more likely to lead to development of neurological events than echogenic ones [1], [2]. Furthermore, carotid plaque echomorphology has been found to be associated with the type of clinical symptoms. Echolucent plaques have been related to retinal symptoms, intermediate echogenic plaques to cerebrovascular symptoms and mainly echogenic plaques to asymptomatic status [3].

Plaque echogenicity can be analyzed with a number of techniques. Wilhjelm et al. [4] in a study with 52 patients scheduled for endarterectomy, presented a quantitative comparison between subjective classification of the ultrasound images, first- and second-order statistical features, and histological analysis of the surgically removed plaque. Some correlation was found between the three types of information where the best performing feature was found to be the contrast – a second-order statistical feature. Asvestas et al [5] estimated the fractal dimension using the k-th nearest neighbor method in ten symptomatic and nine asymptomatic subjects and found it significantly lower in the asymptomatic group. Christodoulou et al [6] estimated texture features of B-mode ultrasound images of carotid atheromatous plaque using first-order statistics, spatial grey level dependence matrices, grey-level difference statistics, neighborhood grey tone difference matrix, statistical feature matrix, Laws texture energy measures, fractal dimension texture analysis, Fourier power spectrum and shape parameters.

The two-dimensional wavelet transform is an efficient mathematical tool for the texture analysis of medical images. It has been shown that the scale/frequency approach based on the wavelet transform is appropriate for texture feature extraction from ultrasound images [7]. Wavelet-based texture analysis using the Haar wavelet has been used to differentiate viable from non-viable myocardium from echographic images [8]. In addition to this, a nonseparable quincunx wavelet transform using the energies of the transformed regions has been used to characterize texture of diffuse liver disease from B-mode ultrasound [9].

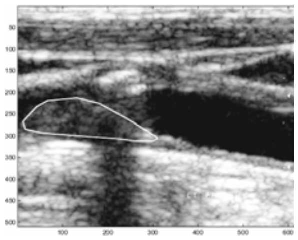
The purpose of this paper was a/ to assess the efficacy of texture analysis methods in characterizing atheromatous plaque and b/ to determine which analytical method or combination of methods provides the most accurate representation of plaque type.

ISSN: 1727-1983

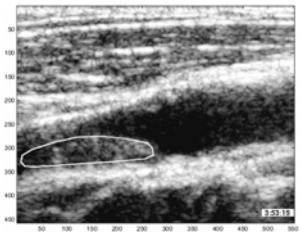
Materials and Methods

Subjects and procedures for image acquisition: A total of 17 subjects, who where recruited from patients referred to the Irvine Laboratory, St Mary's Hospital, London for neck arteries scanning, were selected for the study. The above population provided a total of 19 carotid arteries with an atherosclerotic plaque on the vessel wall (for 2 of the investigated subjects both carotid arteries were studied). Among these, 10 plaques were symptomatic (ages 50-85 years, mean 67,9 years, 2 females) and 9 were asymptomatic (ages 50-90 years, mean 67.6, 6 females). Symptoms include stroke, hemispheric transient ischemic attack and amaurosis fugax, in proportion 30%, 40%, and 30% respectively. There was no significant difference in the degree of stenosis between the two groups of subjects (t-test, p=0.93).

For each subject, a scan sequence was recorded with an ATL (Advanced Technology Laboratory) Ultramark 4 Duplex scanner and a high resolution 7.5 MHz linear scan head. Scanner settings (Dynamic range 60dB, 2D grey map, persistence low, frame rate high) were set at the beginning of the recording and not altered during the procedure. These settings were common for all investigations. Carotid arteries were imaged in longitudinal section, as this section provides more information about the vessel wall. The sequences were recorded at a rate of 25 frames/sec for 3 seconds during breath holding. The images were transferred to a magnet optical disc and then copied to a compact disc. Then they were copied to a personal computer for further analysis. Figure 1 show examples of images from a symptomatic and an asymptomatic subject.



(a)



(b)

Fig. 1. Examples of B-mode ultrasound images of (a) a symptomatic and (b) an asymptomatic carotid atheromatous plaque. The numbers correspond to the number of pixels from the top and left sides of the image. The plaque boundary was outlined by an expert on the histogram equalized version of the image, because this version enhances visualization of structures of interest.

Texture analysis of ultrasound images: Texture characteristics of atheromatous plaques were estimated using ANALYSIS, a modular software system designed to assist interpretation of medical images [10]. ANALYSIS allows image pre-processing, manual and automatic segmentation of regions of interest, estimation of motion from sequences of images, extraction of texture features, dimensionality reduction and clustering using fuzzy c-means. The wavelet transform, the fractal dimension and the second order statistics were used to estimate texture from ultrasound images. These techniques are briefly described below.

Wavelet Transform: The data provided by the intensities of an array of pixels that make up an image are in two dimensional form. In order to perform a wavelet-based parametric characterization for texture image analysis two dimensional discrete wavelet transforms must be used. In this way we can extract information about the low and high frequencies of an image at every resolution. Therefore if the frequency spectrum is decomposed appropriately, different textures will result into different features.

The 2D wavelet transform is actually two separate 1D wavelet transforms. The first transform is performed along each row of the image. The second transform is performed on each column of the resulting image. The wavelet coefficients obtained are called the sub-images at every resolution. These sub-images are basically an approximation image and three detail images, the horizontal, vertical and diagonal (Fig. 2). By adding the image details at an arbitrary scale to the approximation image at that scale we get the image approximation at an increased resolution (i.e. at a smaller scale). This is called multiresolution representation [11].

The following features characterizing image texture were extracted from the wavelet coefficients:

Wavelet Signature Energy: $\frac{1}{N^2}\sum_{i,j=1}^{N} C_s^d(i,j)^2$

Shannon Entropy: $-\sum_{i,j=1}^{N} C_s^d(i,j)\log C_s^d(i,j)$

Average l_1 - norm: $\sum_{i,j=1}^{N}\left|C_s^d(i,j)\right|$

Standard deviation: $\sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}\left(C_s^d(i,j)-Mean\right)^2}$

where

$$Mean = \frac{1}{N^2}\sum_{i,j=1}^{N} C_s^d(i,j)$$

where $C_s^d(i,j)$ are the wavelet coefficients for $d = h, v, d$ (horizontal, vertical and diagonal) at scale $s = 1,2,\ldots,6$.

Each NxN image was decomposed up to 6 scales using an orthogonal, near symmetric and compactly supported mother wavelet, the Coiflet5 [12]. The approximation sub-images were not used for texture analysis since they are just a rough estimate of the original image and capture the variations induced by lighting and illumination [13]. Hence, a total of 72 wavelet based texture features were extracted for each plaque.

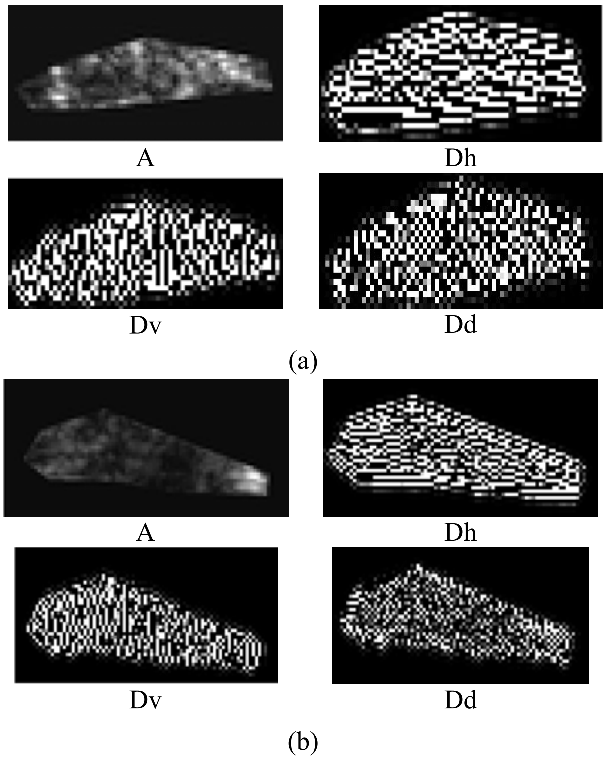


Figure 2: Examples of wavelet decomposition of a B-mode ultrasound image of a (a) symptomatic and (b) asymptomatic plaque. A: Approximation image. Dh: Horizontal detail image. Dv: Vertical detail image. Dd: Diagonal detail image. All images correspond to scale 2.

Fractal Dimension: Many natural surfaces have a statistical quality of roughness and self-similarity at different scales. Fractals are very useful in modeling these properties in image processing. The definition of the fractal dimension is based on the concept of self-similarity. Given a bounded set A in a Euclidean n-space, the set A is said to be self-similar when A is the union of N distinct (non-overlapping) copies of itself, each of which has been scaled down by a ratio of r. The fractal dimension D is related to the number N and the ratio r as follows:

$$D = \frac{logN}{log(1/r)}$$

The fractal dimension gives a measure of the roughness of a surface. For an image, the fractal dimension is a noninteger number between 2 and 3. Intuitively, the larger the fractal dimension, the rougher the texture. There are a number of methods for estimating the fractal dimension. In this study, the fractal dimension was estimated using the Differential Box Counting (DBC) method, a modification of the traditional box counting method [14].

Second-order statistics: Second-order statistics are derived from angular nearest-neighbor spatial-dependence matrices, also known as co-occurrence matrices [15]. The relative frequencies P(i,j,d,θ) with which two neighboring pixels with gray levels i and j at a given distance d, and orientation θ, occur on the image, are used to construct the co-occurrence matrices. A distance of one pixel was chosen because the regions of interest were small (150-200 pixels). Co-occurrence matrix for each orientation (0^o, 45^o, 90^o, 135^o) were formed and averaged to ensure rotational invariance. A total of 14 textural measures were estimated from the co-occurrence matrix, including angular second moment, contrast, correlation, variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation (2 features) and maximum correlation coefficient.

Dimensionality reduction: To reduce the dimensionality of the texture feature vector, ANOVA (ANalysis of VAriance) statistics may be applied [16]. The 'f-ratio' of the class-to-class variance over the within-class variance is estimated to select features significantly different between tissue types. Features that produced an 'f-ratio' greater than a set threshold (in our case the threshold was equal to 4) were retained to the feature vector while the remaining were discarded.

Clustering using fuzzy c-means: An unsupervised classification method, namely fuzzy c-means [17], was used to cluster texture features. For each investigated feature, a vector is created with points corresponding to the feature values for each subject. The fuzzy c-means algorithm assigns data points with similar characteristics to a pre-defined number of classes. By iteratively updating the clusters' centers and the membership grades for each data point, the algorithm iteratively moves the cluster center to the "correct" position for each data set. The iteration is based on minimizing an objective function that represents the distance of each data point to a cluster center, weighted by the membership grade of the specific data point. Each vector is assigned to the cluster corresponding to the maximum of its membership function values. The output of the algorithm consists in the centers of the clusters, and the values of the membership functions for each vector. Each vector is assigned to the cluster corresponding to the maximum of its membership function values. Two classes were used in this study, corresponding to symptomatic and asymptomatic plaques.

Results

A total of 87 features (72 features derived from wavelet transform, 14 second-order statistical features and the fractal dimension) were estimated for each plaque. After dimensionality reduction, 4 features were significantly different between the two groups. These included standard deviation scale 1 derived from the horizontal detail image (STD1h), standard deviation at scale 2 derived from the horizontal detail image (STD2h), information measure of correlation (IMC) and the fractal dimension. Their average values (± standard deviations) are shown in Table 1. As we can see, STD1h, STD2h and the fractal dimension were higher in the symptomatic plaques. On the other hand, IMC was higher in the asymptomatic plaques.

Clustering using fuzzy c-means was performed for all possible combinations of pairs of texture features. The performance of the clustering procedure was estimated in each case, which is an index of the ability of the features to characterize different tissue types. Table 2 shows the centers of the clusters for 6 combinations of texture features and the performance of clustering procedure. Examples of clustering for four combinations of texture features are depicted in Fig. 3.

Table 1: Texture features of symptomatic and asymptomatic plaques STD1h: standard deviation at scale 1 and horizontal detail image. STD2h: standard deviation at scale 2 and horizontal detail image. .IMC: Information Measure of Correlation.

Texture Feature	**Symptomatic**	**Asymptomatic**	**f-ratio**	**p- value**
Wavelet Texture Analysis				
STD1h	1.70 ± 0.74	1.10 ± 0.48	4.28	0.05
STD2h	4.27 ± 1.47	2.95 ± 1.16	4.63	0.04
Second Order Statistics				
IMC	0.93 ± 0.018	0.95 ± 0.014	7.85	0.01
Fractal Dimension	2.20 ± 0.09	2.13 ± 0.04	5.08	0.03

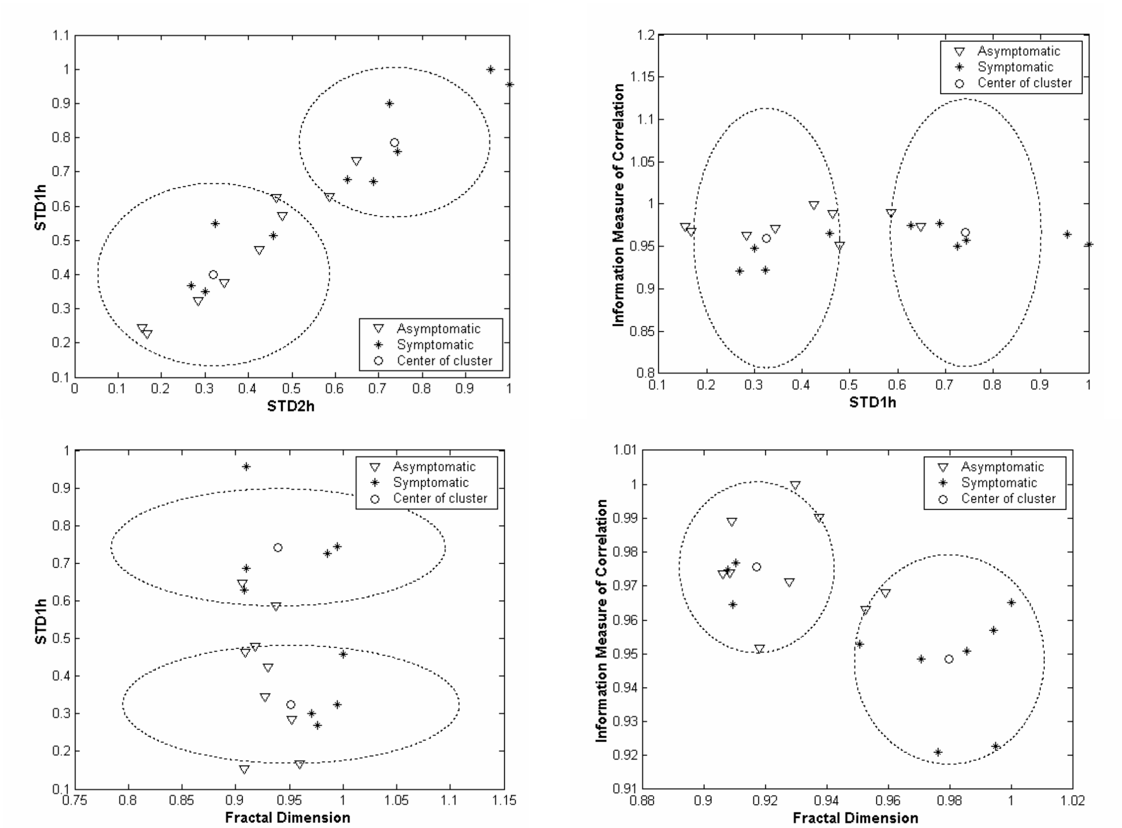


Figure 3: Example of clustering using fuzzy c-means for four combinations of texture features. In the graphs, the values of the features were normalized to better illustrate their distribution in the feature space.

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Table 2: Centers of clusters using fuzzy c-means. STD1h: standard deviation at scale 1 and horizontal detail image. STD2h: standard deviation at scale 2 and horizontal detail image. IMC: Information Measure of Correlation. FD: fractal dimension. Perf: Performance of clustering

Feature Combination	Class 1	Class 2	Perf
STD1h-STD2h	(2.01, 4.91)	(0.87, 2.43)	68%
STD1h-IMC	(0.91, 0.93)	(2.07, 0.95)	68%
FD-IMC	(2.26, 0.93)	(2.11, 0.95)	74%
STD2h-IMC	(4.84, 0.95)	(2.37, 0.94)	58%
STD2h-FD	(2.19,2.37)	(2.16,4.84)	58%
STD1h-FD	(0.91, 2.19)	(2.07 2.16)	68%

Discussion

Image texture has been widely used to characterize biological tissue. In the small group of images that were investigated in this study, 4 texture features were found to significantly differentiate between symptomatic and asymptomatic plaques. The obvious conclusions that these features should be used in diagnosis of carotid atherosclerosis should be further corroborated by larger scale studies. Estimates of tissue texture may be used in a number of studies, including a/ modeling of the mechanical behavior of normal and abnormal tissue, and b/ drug assessment.

More specifically, wavelet-based texture analysis showed that features estimated from the horizontal detailed matrices were found significantly different between symptomatic and asymptomatic plaques. This may indicate that texture patterns in the horizontal direction better characterize plaque tissue. In addition to this, entropy and energy estimated from the horizontal detail images at scales 1 and 2 were found to have p-values close to the limit of statistical significance (0.05). This finding suggests that statistical significance may be increased in larger groups of subjects are used. Alternatively, the application of a resampling method (eg. Bootstrapping) in the existing sample may also enhance statistical differences between groups.

The fractal dimension, as calculated with the DBC method, was significantly lower in the asymptomatic compared with the symptomatic plaques. These findings show that the symptomatic carotid atheromatous plaques, have a rougher appearance in ultrasound images. Moreover, within the small group of subjects that was investigated, the information measure of correlation, estimated using second order statistics, was significantly higher in asymptomatic plaques. This indicates that the linear dependency of gray levels of neighboring pixels is higher in asymptomatic plaques.

Conclusions

Three different methods for texture analysis of the atheromatous plaques from B-mode ultrasound images were studied. Texture analysis using 2-D wavelet transform resulted in two texture features significantly higher in symptomatic plaques. In addition to this, fractal dimension and information measure of correlation, estimated using second-order statistics, were significantly different between symptomatic and asymptomatic subjects. After clustering using fuzzy c-means, the combination of fractal dimension and information measure of correlation exhibited the best performance in differentiating symptomatic and asymptomatic cases.

Acknowledgement

Special thanks are due to Professor Andrew N.Nicolaides and the staff of the Irvine Laboratory, St. Mary's Hospital, London, for their contribution in recording the image sequences.

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ISSN: 1727-1983

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 ISSN: 1727-1983