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STATISTICAL FEATURE ANALYSIS OF ULTRASOUND CAROTID IMAGES FOR ASYMPTOMATIC PLAQUE IDENTIFICATION

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Abstract---Carotid plaques have been associated with neurological, cerebrovascular and cardiovascular disease symptoms. High-resolution ultrasound scanning images can provide information about degree of carotid artery plaque. It also illustrates the characteristics of the arterial wall including the size and consistency of atherosclerotic plaques. The aim of this study is to extract the features from the ultrasound plaque image based on the technique multiresolution analysis. In this analysis combination of wavelet transform and Gabor transform are performed to the plaque image. At the end of analysis, Grey Level Run length Statistics features are extracted. These features improve the ability to identify the plaque type for further classification process.

Keywords---Carotid plaques, Ultrasound scanning, Wavelet Transform, Gabor Transform, Multiresolution analysis.

I.INTRODUCTION

In human body, Carotid artery is the large artery whose pulse can be felt on both sides of neck under the jaw. There are two common carotid arteries which are internal and external. Internal carotid artery supplies blood to face, scalp and neck. External carotid artery supplies blood to brain. One of the Carotid artery diseases is Atherosclerosis which is caused by waxy substance called plaque builds up in arteries. It affects any artery in the body. Plaque builds up in coronary artery, heart attack can occur. Plaque builds up in the carotid artery, a stroke can occur. Carotid plaques are the symptom for neurological disease, cerebrovascular disease and cardiovascular disease . It is essential to study the texture characteristic of carotid plaque.

Ultrasound imaging holds a prominent position in the analysis of carotid plaques. Compared to other imaging techniques, Ultrasound imaging allows accurate identification and evaluation of vessels. Ultrasound has a number of advantages, including capability of forming real time imaging, noninvasiveness, widespread availability, short examination time, lack of radiation exposure and low cost. High resolution vascular B-mode (B-Brightness) type of ultrasound scanning used for carotid plaque imaging. It provides information about the size and consistency of the atherosclerotic plaques.Very small difference in echogenicity also possible to visualize.

Images usually contain informations at multiple resolutions.Multiresolution analyses, including wavelet-based methods are useful framework for many image analyses. Wavelet models have been used in a number of texture classification tasks in real medical images.Wavelet transforms, which decompose appropriately the frequency content of the image and reveal plaque texture characteristics free from the effect of noise. The result of the wavelet transform decomposition gives image into detailed sub images.Gabor transform (GT), a family of linear, frequency and orientation selective filters particularly appropriate for texture representation and discrimination, have been used to characterize carotid plaque tissue from B-mode ultrasound.

The previous paper shown that the texture features based on second order statistics spatial gray level dependence matrices (SGLDM) improves stroke prediction with best classification results of 77 ± 1.8%.In this paper, Gabor transform performed to the result of wavelet transform decomposition detailed sub images. From the result image of Gabor transform, GLRS(Gray Level Run Length Statistics)features are extracted for the further process of effective classification of the plaque type. This framework is explained in the block diagram.

1.1. Block diagram

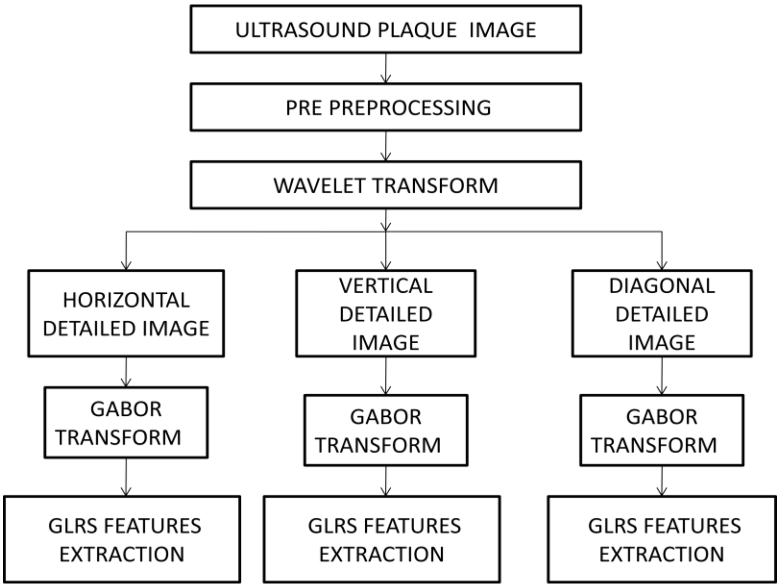

Figure 1. overall block diagram

II. METHODS AND MATERIALS

2.1. Multiresolution Analysis

It is the technique of analysis and representation of image at more than one resolution. Features may undetected at one resolution and detected at other resolution. In this multiresolution technique Wavelet Transform subsequently Gabor Transform(GT) performed to the cropped carotid plaque image.

2.1.1 Preprocessing

The first step of Multiresolution analysis starts with preprocessing. In this process, from the ultrasound carotid artery scanned image, plaque part is cropped manually.

2.1.2. Discrete Wavelet Transform

In this 2-D Discrete wavelet transform, single-level two-dimensional wavelet decomposition with respect to particular wavelet is performed to the input image.

Scaling and Wavelet function:

The DWT of an image is defined as its inner product with a family of functions, $\varphi_{j,k}(t)$ and $\psi_{j,k}(t)$.The functions form an orthonormal set of vectors, a combination of which can completely define the input, and hence, allow its analysis in many resolution levels j

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^{j}t-k) \qquad (1)$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{j}t-k) \qquad (2)$$

The functions $\varphi_{j,k}(t)$ and $\psi_{j,k}(t)$ consist of versions of the prototype scaling $\varphi(t)$ and wavelet $\psi(t)$ functions, discretized at level j and at translation k.

Selection of Basis Functions:

The selection of the basis function based on the desired function properties.The wavelet function selected for small support width because the size of the investigated images are small.The support of

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a wavelet quantifies its localization in time and frequency domain.In this 2-D DWT,coiflets basic function is used. This function is orthogonal and near symmetric.The property of orthogonal maintains the same amount of energy noise at each level.

In this single level decomposition,level one coefficients are approximation(cA_1) and horizontal, vertical and diagonal details(cH_1,cV_1 and cD_1) generated. The level-one approximation and detailed images (A_1, H_1, V_1, and D_1) are constructed from the coefficients cA_1, cH_1, cV_1, and cD_1.The detail subimages contain the textural information in horizontal,vertical and diagonal orientations.

The approximation subimages are not used for texture analysis because they are the rough estimate of the original image.The detail subimages are only used in further analysis process and feature extraction process.

2.1.3. Gabor Transform

Gabor transform (GT), a family of linear, frequency, and orientation selective filters particularly appropriate for texture representation and discrimination, have been used to characterize carotid plaque.The GT of an image consists in convolving that image with the Gabor function, i.e., a sinusoidal plane wave of a certain frequency and orientation representations of Gabor filters are similar to those of the human visual system, rendering them appropriate for texture segmentation and classification.

Formula for Gabor Transform:

In this paper, Gabor features are extracted from Gabor filtered image for 5 scales and 7 orientations.M,N are number of scale & orientations, Uh, Ul are highest & lowest central frequencies scale factor a:

$$a=\left(\frac{U_h}{U_l}\right)^{\frac{1}{M-1}} \qquad (3)$$

modulation frequency Wmn:

$$W_{m,n} = a^m . U_l \qquad (4)$$

Sigma x:

$$\sigma_{x,m,n} = (a+1)\sqrt{2\ln 2} \Big/ 2\pi . a^m (a-1) U_l \qquad (5)$$

Sigma y:

$$\sigma_{y,m,n} = \frac{1}{2\pi \tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h^2}{2\ln 2} - \left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}} \qquad (6)$$

x, y values (Here θ represents theta):

$$\overline{x} = a^{-m}(x\cos\theta + y\sin\theta) \qquad (7)$$

$$\overline{y} = a^{-m}(-x\sin\theta + y\sin\theta) \qquad (8)$$

Gabor wavelet function:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\cdot\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)} . e^{j2\pi W_x} \qquad (9)$$

Gabor filter function:

$$G_{mn}(x,y) = \sum_s \sum_t I(x-s,y-t) . \psi_{mn}^*(s,t) \qquad (10)$$

Where $\psi_{mn}^*(s,t)$ represents the complex conjugate of wavelet function $\psi(x,y)$ at the mask values.The Gabor filtered image is obtained by convolving the wavelet decomposition sub image with complex conjugate of wavelet function.

III. RESULTS

3.1. Carotid Ultrasound plaque Images

Input image is a carotid plaque image captured by B-mode ultrasound scanner.In the ultrasound carotid artery image plaque part is cropped manually.

A. Asymptomatic Plaque Image and Cropped Image:

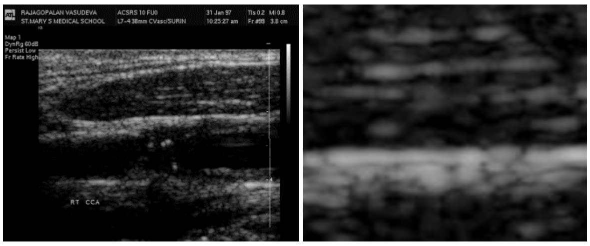

Figure 2. Asymptomatic image

B. Wavelet Transform Output:

Discrete Wavelet Transform is performed to the cropped plaque part of asymptomatic type.The result contain decomposed detail sub images (approximation, horizontal, vertical and diogonal).

In the decomposed detail sub images, approximation image is the overall approximated image of the original.For the reason,approximation image is not considered in the next step of analysis.

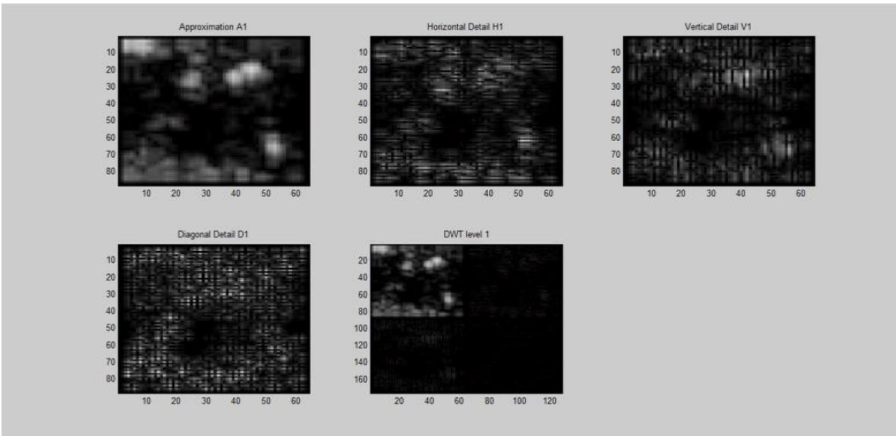

Figure 3. Asymptomatic wavelet transform output

3.Gabor Transform Output:

Gabor transform is performed to the horizontal,vertical and diagonal detail subimages of asymptomatic carotid plaque.The result contain 35 subimages for five scales and seven orientation values of horizontal detail subimage.

The result contain 35 subimages for five scales and seven orientation values of vertical detail subimage.

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Figure 5. Asymptomatic vertical detail subimage

The result contain 35 subimages for five scales and seven orientation values of diagonal detail subimage.

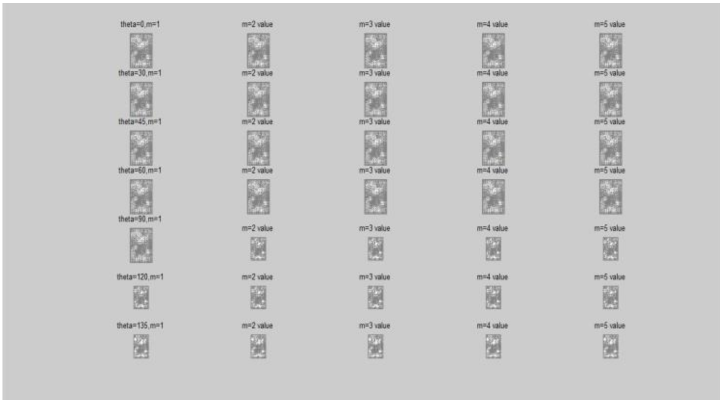

Figure 6. Asymptomatic diagonal detail subimage

IV. FEATURE EXTRACTION

4.1. Gray Level Run length Statistic features(GLRS):

Run length texture feature extraction algorithm that preserves much of the texture information in run length matrices and significantly improves image classification accuracy.

Gray Level Run length Statistic features are extracted from the result of Gabor filtered detailed sub images.In Gray Level Run length Statistic feature set:

- SRE(Short Run length Emphasis)
- LRE(Long Run length Emphasis)
- GLN(Gray Level Nonuniformity)
- RLN(Run length Nonuniformity)
- RP(Run length Percentage)
- LGRE(Low Gray level Runlength Emphasis)
- HGRE(High Gray level Runlength Emphasis).

4.1.1. SRE(Short Run length Emphasis):

It measures the distribution of short runs, highly dependent on the occurrence of short runs, expected large for fine textures.

$$SRE=\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{j^2} \qquad (11)$$

Where,

n_r-Total number of runs.

4.1.2. LRE(Long Run length Emphasis):

It measures the distribution of long runs, highly dependent on the occurrence of long runs, expected large for coarse structural textures.

$$LRE=\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j)*j^2 \qquad (12)$$

4.1.3. GLN (Gray Level Non uniformity):

It measures the similarity of gray level values throughout the image, expected small if the gray level values are alike through out the image.

$$GLN=\frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N}P(i,j)\right)^2 \qquad (13)$$

4.1.4. RLN (Run Length Non uniformity):

It measures the similarity of the length of runs through out the image, expected small if the run lengths are alike through out the image.

$$RLN=\frac{1}{n_r}\sum_{j=1}^{N}\left(\sum_{i=1}^{M}P(i,j)\right)^2 \qquad (14)$$

4.1.5. RP (Run length Percentage):

It measures the distribution of runs of an image in a specific direction.

$$RP=\frac{n_r}{n_p} \qquad (15)$$

Where,

n_p-Total number of elements

4.1.6. LGRE (Low Gray Level Run length Emphasis):

It measures the distribution of low gray level values, expected large for the image with low gray level values.

$$LGRE=\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{i^2} \qquad (16)$$

4.1.7. HGRE (High Gray Level Run length Emphasis):

It measures the distribution of high gray level values, expected large for the image with high gray level values.

$$HGRE=\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j)*i^2 \qquad (17)$$

V.CONCLUSION

In this paper, Gray Level Run Length Statistic features are extracted from the result of Gabor transformed wavelet decomposed detailed sub images of asymptomatic carotid plaque. These feature values provide the better identification of asymptomatic plaque type.

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