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An efficient texture feature extraction method for classification of liver sonography based on Gabor Wavelet

A. Ahmadian[1], A. Mostafa[2], M. D. Abolhassani[3], N. Riahi Alam[4], M. Gitti[5]
[1,2,3,4] Department of Medical Physics & Biomedical Systems, Tehran University of Medical Sciences, Tehran, Iran
[5] Medical Imaging Center, Imam Khomeini Hospital, Tehran, Iran
e-mail[1]: ahmadian@sina.tums.ac.ir

Abstract: ***In this paper we proposed a new method for texture classification of ultrasonic liver images based on Gabor wavelet. It is well known that Gabor wavelets attain maximum joint space-frequency resolution which is highly significant in the process of texture extraction in which the conflicting objectives of accuracy in texture representation and texture spatial localization are both important. This fact has been explored in our results as it shows that the classification rate obtained by Gabor wavelet is higher that those obtained using dyadic wavelets. The fearure vector consists of .. parameters from Gabor wavelets which is relatively small compared to other methods. This has a significant impact on the speed of retrieval process. The proposed algorithm applied to discriminate ultrasonic liver images into three disease states that are normal liver, liver hepatits and cirrhosis. In our experiment 45 liver sample images from each three disese states which already proven by needle bioposy were used. We achieved the classification rate 85% in the distinction between normal and abnormal liver images and 80% in the distinction between cirrhosis and hepatitis liver images. Based on our experiments, the Gabor wavelet is more appropriate than dyadic wavelets for texture classification as it leads to higher classification accuracy.***

Keywords—**Texture Classification, Feature extraction, Gabor wavelet, Texture analysis.**

I. INTRODUCTION

Ultrasonic imaging has gained widespread acceptance as an effective diagnostic tool to visualize organs and soft tissues in human abdominal wall. Ultrasonic echoes from human tissues displayed as a B-scan image form a texture pattern that is a characteristic of both the imaging system and the tissue that is being imaged.

One application of diagnostic ultrasound is liver imaging. Ultrasound B-scan images present various granular structures as texture. Therefore, the analysis of ultrasonic image will lead to the problem of texture classification. Texture is an image feature that provides important characteristics for surface and object identification from image [1]. Texture analysis is a major component of image processing and is fundamental to many applications such as remote sensing, quality inspection, medical imaging, etc.

In chronic liver disease, the severity of infected patients may vary from healthy carrier to cirrhosis. The conventional diagnostic method for patients depends mainly on needle biopsy of the liver which is an invasive method. Bear in mind that the pathological measurement of these diseases can be biased due to sampling error in the biopsy specimen. Therefore, developing a reliable noninvasive method of evaluating histological changes in sonograms will be a major advance in diagnosis and monitoring of chronic liver diseases.

In texture analysis, the most difficult aspect is to define a set of meaningful features that explores the characteristics of the texture. There have been several approaches to this problem such as spatial gray-level dependence matrices [1], the Fourier power spectrum [2], the gray level difference statistics [3], etc. Although they yield a promising result to nature texture analysis, but they fail to classify ultrasonic liver images adequately.

Recently, multiscale filtering methods have shown significant potential for texture description, where advantage is taken of the spatial-frequency concept to maximize the simultaneous localization of energy in both spatial and frequency domains [2].

The use of wavelet transform as a multiscale analysis for texture description was first suggested by Mallat [3,4]. Recent developments in the wavelet transform provide good multiresolution analytical tool for texture analysis and can achieve a high accuracy rate.

Most of previous works on wavelet transform have focused on dyadic wavelet transform which applies one-dimensional wavelet transform to both rows and columns of image, separately[5]. In this paper we used non-separable Gabor wavelet for texture classification and we compared it's effectiveness with traditional dyadic wavelet transform.

II. REVIEW OF GABOR WAVELETS

A. Gabor Functions and Wavelets

A 2D Gabor function g(x,y) and its Fourier transform G(u,v) can be written as [6]

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left(\frac{-1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right) \qquad (11)$$

$$G(u,v) = \exp\left(\frac{-1}{2}\left(\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right)\right) \qquad (12)$$

where

$$\sigma_u = \frac{1}{2\pi\sigma_x} \quad , \quad \sigma_v = \frac{1}{2\pi\sigma_y} \qquad (13)$$

Gabor functions form a complete but non-orthogonal basis set. Expanding a signal using this basis provides a localized frequency description.
A class of self-similar functions referred to as *Gabor wavelets*, is now considered. Let *g(x,y)* be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x,y) through the generating function :

$$g_{mn}(x,y) = aG(x',y') \qquad (14)$$
$$a > 1$$
$$m,n = \text{Integers}$$

and

$$x' = a^{-m}(xCos\theta + ySin\theta) \qquad (15)$$
$$y' = a^{-m}(-xSin\theta + yCos\theta) \qquad (16)$$

where $\theta = \frac{n\pi}{k}$

and k is the total number of orientations. The scale factor a^{-m} is meant to ensure that the energy is independent of *m*.

B. Gabor Filter Design

The non-orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let U_l and U_h denote the lower and upper center frequencies of interest. Let *K* be the number of orientations and *S* be the number of scales in decomposition. Then the design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other as shown in figure (1).

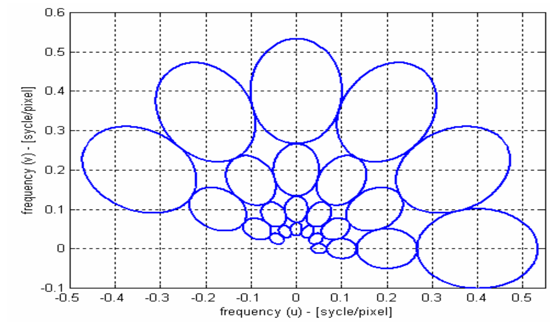

Figure 1: The contours indicate the half-peak magnitude of filter responses in Gabor filter dictionary. The filter parameters are U_h=0.4, U_l=0.05, *M*=4, and *N*=6.

This results in the following formulas for computing the filter parameters σ_u and σ_v.

$$a = \left(\frac{U_h}{U_l}\right)^{\frac{-1}{S-1}} \qquad (17)$$

$$\sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}} \qquad (18)$$

In order to eliminate sensitivity of filter response to absolute intensity values the real components of 2D Gabor filters are biased by adding a constant to make them zero mean.

III. Feature Extraction & Classification

A. Feature Extraction& classification with dyadic wavelet transform

First every input image is transformed to wavelet domain. Then the energy of each subimage is calculated from

$$E_i = \frac{1}{M\times N}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i^{\,2}(x,y) \qquad (19)$$

where, $I_i(x,y)$ denotes an image obtained in $\boldsymbol{i}^{th}$ subband , with resolution $M\times N$.
The distance vector D between test image and $\boldsymbol{i}^{th}$ reference texture is

$$\vec{D}_i = \left|\vec{E}_i - \vec{E}_t\right| \qquad (20)$$

where E_i and E_t are the energies of $\boldsymbol{i}^{th}$ reference texture and test texture. The distance number *d* is calculated from

$$d_i = \sum_j D_i(j) \qquad (21)$$

The test image is referred to class k if d_k is the minimum value of d_i for test image.

B. Feature Extraction& classification with Gabor wavelet transform

Given an image *I(x,y)*, its Gabor wavelet transform is defined as

$$W_{mn}(x,y) = \int I(x_1, y_1) g^{*}_{mn}(x - x_1, y - y_1) dx_1 dy_1 \quad (22)$$

where * indicates the complex conjugate. We assume the local texture regions are spatially homogeneous. The mean μ_{mn} and standard deviation σ_{mn} of the magnitude of transform coefficients are used to represent the regions for classification :

$$\mu_{mn} = \iint \left| W_{mn}(x,y) \right| dxdy \quad (23)$$

$$\sigma_{mn} = \sqrt{\iint \left(\left| W_{mn}(x,y) \right| - \mu_{mn} \right)^2 dxdy} \quad (24)$$

A feature vector is now constructed using μ_{mn} and σ_{mn} as feature components.

Let $\bar{f}^{\,i}$ and $\bar{f}^{\,j}$ represent the feature vector of test and reference texture, respectively. Then the distance between two textures in the feature space is defined to be

$$d(i,j) = \sum_i \sum_j d_{mn}(i,j) \quad (25)$$

where

$$d_{mn}(i,j) = \left| \frac{\mu^{(i)}_{mn} - \mu^{(j)}_{mn}}{\alpha(\mu_{mn})} \right| + \left| \frac{\sigma^{(i)}_{mn} - \sigma^{(j)}_{mn}}{\alpha(\sigma_{mn})} \right| \quad (26)$$

The test image is referred to class k if d_k is the minimum value of d_i for test image.

IV. EXPERIMETNAL RESULTS

In this study, ultrasonic images were captured from … with a 3.5-MHz transducer. All images were standardized to the same mean intensity. We used 45 image cases of normal liver, hepatitis, and cirrhosis, identified by liver biopsy. For each image, an area of interest with ..x.. pixels is selected. Each area of interest is chosen to include only liver tissue without major blood vessel or hepatic duct.

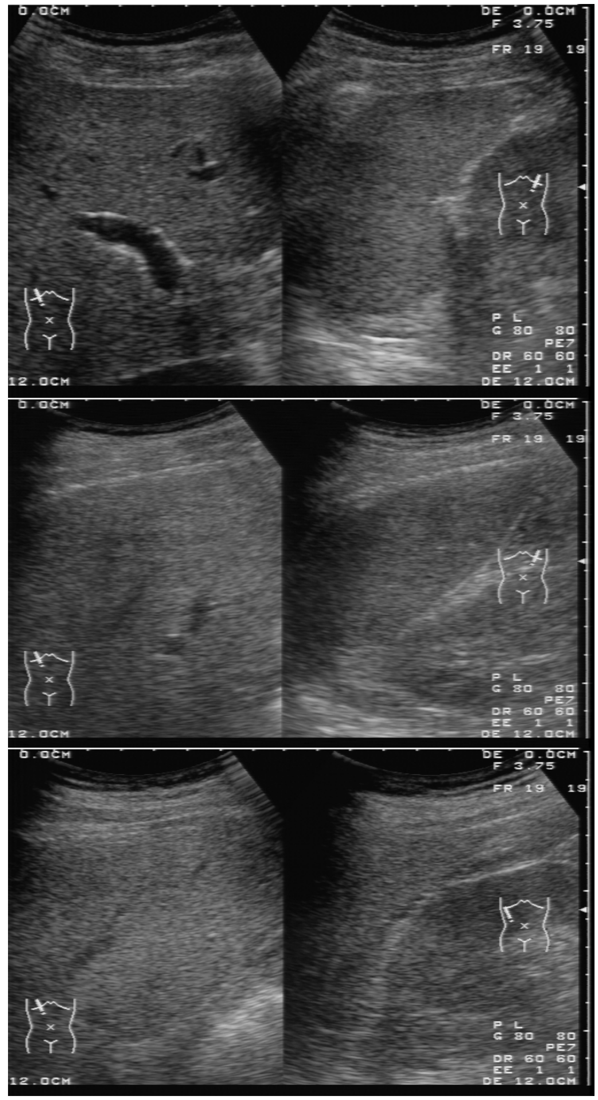

Figure 2: textures used for classification algorithms

In the first step we applied dyadic wavelet transform (Daubechies and Symlet wavelet filters) for classification algorithm. The wavelet filter parameters were tuned to achieve the best result. We have already shown that the wavelet filter parameters such as regularity, phase linearity, etc have a great impact on the performance of the classification algorithms [7].

We used the quantity named "classification rate" defined as below to compare the results.

$$\text{Classification rate} = \frac{\text{Number of Textures Classified Truely}}{\text{Total Number of Classified Textures}} \quad (27)$$

The classification rate achieved by dyadic wavelet was about 86%.

In the second step we applied Gabor wavelet to the textures. To get the best result, the Gabor parameters were tested for different values of the number of scales *(S)* and the number of orientations *(K)*. The classification rate computed for each setting. The results are presented in Table (1). As it suggests the total number of bands at all orientations is important for texture classification since it improves the process of texture discrimination by using more features. Obviously, the cost for this improvement is an increase in computational time.

An effective classification system should decrease the possibility of misclassification, especially for the false negative one. The false-negative rate is the probability of the misclassification that the patients are classified with less severe disease that the actual diagnosis. High false-negative rate represents the danger to underestimate severity of patient, when the clinical doctors used the texture classification system. From Table 2 we find that the false-negative rate is only by using Gabor wavelet. The results are superior to those obtained by dyadic wavelets.

The receiver operating characteristics (ROC) analysis is based on statistical decision theory and has been used extensively to the evaluation of diagnosis. The ROC curves represent s the relation between the true-positive fraction (TPF) and false-negative fraction (FPF) with the variations of decision threshold. The TPF and FPF denote the fraction of patients having the diseases in question that are diagnosed as positive and the fraction of patients actually without the disease in question that are diagnosed as positive, respectively. Furthermore, the area under the ROC curve is a powerful index for assessing the classification performance. A higher area reflects to the fact that a larger value of TPF is achieved and thus a smaller corresponding value for FPF. In these experiments, all images are divided into two diagnosis groups that are liver hepatitis and cirrhosis and normal liver. The corresponding curves for different texture features are depicted in Fig 2.

Table 1: Classification rate obtained for different values of *S* and *K.*

Number of Scales (S)	*Number of Orientations (K)*	*Classification Rate*
6	6	86%
8	6	93%
6	8	93%

Table 2: Results of Rotation, and Brightening of input images on classification rate for dyadic and Gabor wavelet

Input images	*Dyadic wavelet classification rate*	*Gabor wavelet classification rate*
Original Textures	86%	93%
Brightened Textures	73%	86%

V. Discussion

In this paper a new texture analysis method based on Gabor wavelet is proposed to classify ultrasonic liver images into three classes of liver diseases that are normal liver, hepatitis and liver cirrhosis. As the experimental results clearly show that the Gabor wavelet is more effective for texture classification than dyadic wavelet based method.

One main reason for this is because the dyadic wavelet loses some middle-band information, while the Gabor wavelet preserves them. In the pyramid structured wavelet transform, the spatial frequency plane was decomposed logarithmically. For low-frequency signal, this decomposition in low bands is suitable. However, based on our observation, the most significant information of a texture is mainly located in the middle-frequency bands of wavelet decomposition. Therefore, the above decomposition fails to provide more useful information for texture features. Via Gabor wavelet transform, the spatial frequency plane can combine logarithmic and uniform spacing. Therefore, a more flexible decomposition of the entire frequency band can be achieved which has led to a superior discriminative of texture information.

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