Texture Analysis of Ultrasonic Liver Images Based on Spatial Domain Methods

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***Abstract*—The paper introduces three texture analysis methods of ultrasonic images based on spatial domain method. Feature parameters, including mean, variance, contrast, homogeneity, angular second moment and entropy, are achieved from gray histogram statistic, gray level difference statistic (GLDS), gray level co-occurrence matrix (GLCM). Then the above statistical feature parameters are applied for texture classification by neural network. The Probabilistic Neural Network (PNN) is employed as a classifier to differentiate ultrasonic fatty liver image from normal liver image. Experimental results showed that the joint statistical feature parameters extracted from the three methods achieve good effects.**

Keywords-Texture Analysis; Gray Histogram Statistic; GLDS; GLCM; Feature Parameters; PNN

I. Introduction

Ultrasonic imaging is a popular and non-invasive tool frequently used in diagnosis and prognostication of diseases. The ultrasonic liver images have various granular structures described by texture [1]. Texture is very difficult to give it a definition. This difficulty is demonstrated by the number of different texture definition attempted by vision researchers. A region in an image has a constant texture if a set of local statistics or other local properties of the picture function are constant, slowly varying, or approximately periodic. Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers [2].

One important application of image texture is texture classification using texture feature. Texture classification involves deciding what texture category an observed image belongs to. In order to accomplish this, one needs to have an a priori knowledge of the classes to be recognized. Once this knowledge is available and the texture features are extracted, one then uses classical pattern classification techniques such as neural network to do the classification [2]. Ultrasonic normal liver images and fatty liver images have different granular which could be described by texture feature. Therefore, the analysis of ultrasonic normal and fatty images can be viewed as the problem of texture classification. The major problem of texture classification is feature parameters extraction.

Most of the existing feature extraction methods can be broadly divided into two categories: structural and statistical approaches. The former appears to be appropriate for periodic texture with a low noise level which is seldom encountered in the realistic cases. The statistical approach can also be broadly divided into two categories, which are based on spatial domain and transformed domain. A considerable number of image texture analysis techniques were developed over the years, such as the gray histogram statistics, GLDS, GLCM [3], the fractal dimension texture analysis and the gray run length statistics [4], the above techniques are based on space domain. The popular texture analysis methods based on transformed domain are the Fourier power spectrum and wavelet transform analysis [5]. Each of the above methods has its own peculiarity in performance [6].

Feature parameters extracted from ultrasonic liver images by applying gray histogram statistics can't demonstrate spatial information of the image. Feature parameters extracted by GLDS algorithm just demonstrate 1-dimension station information, while feature parameters based on GLCM can demonstrate 2-dimension station information. In transformed domain methods, feature extraction based on wavelet transform is prior [7]. The follow is the three algorithms mainly used in spatial domain and their effects.

II. Methods

A. Feature Extraction Based on Gray Level Histogram

The feature parameters which derived from the gray level histogram could describe the gray level distribution without considering spatial dependence; therefore the parameters can only describe echo intensity and diffuse variation characteristics of the image. Extracted statistic characteristic parameters, including gray mean, variance, angular second moment and entropy, are computed according to follow formulas: where $p(r)$ is the appearance probability of the gray value *r*.

Mean: $$M = \sum_{r=0}^{L-1} r p(r) \quad (1)$$

Variance: $$V = \sum_{r=0}^{L-1} (r-M)^2 p(r) \quad (2)$$

Angular Second Moment: $ASM = \sum_{r=0}^{L-1} p^2(r)$ (3)

Entropy: $ENT = -\sum_{r=0}^{L-1} p(r) \log_2 p(r)$ (4)

Extracted characteristic parameters from gray histogram could reflect ultrasonic echo intensity and image's uniformity. The defect is that image's space information is lost and image's gray level distribution property could not be reflected. The algorithm based on GLDS and GLCM can effectively overcome this defect.

B. Feature Extraction Based on GLDS

Gray level difference histogram statistical (GLDS): the algorithm is based on the estimation of the probability density $p_\Delta(i)$ of image pixel pairs at a given distance △=(△x,△y) having a certain absolute gray level difference value *i*. The parameters from GLDS can reflect image's texture characteristic by calculating gray difference histogram of a pair of pixels in the image.

Statistical measures are computed on the base of GLDS by using formulas given in the Eqs. (5), (6), (7), (8), where $p_\Delta(i)$ is the appearance probability of the difference value *i*. Each measurement is estimated for the following distance △ =(0,1).

Mean: $M = \sum_{i=1}^{m} i p_\Delta(i)$ (5)

Contrast: $CON = \sum_i i^2 p_\Delta(i)$ (6)

Angular Second Moment: $ASM = \sum_i [p_\Delta(i)]^2$ (7)

Entropy: $ENT = -\sum_{r=0} p_\Delta(i) \log_2 p_\Delta(i)$ (8)

C. Feature Extraction Based on GLCM

GLCM method: it is do some investigation and statistics to all pixels of image. It can describe image gray level's space characteristic and spatial correlation at the same time [7]. The GLCM of an image is based on the estimate of the second-order joint probability density $P(g_1, g_2 | d, \theta)$. Each value $P(g_1, g_2 | d, \theta)$ represents the probability that two different angle θ and distance *d*, will have gray values g_1 and g_2 respectively. When texture is coarse and *d* is small compared to the texture elements ("speckle pattern") then the pairs of points with distance *d* will have similar gray levels, so the points on the main diagonal of the matrices $P(g_1, g_2 | d, \theta)$ will have great values. On the other hand, if texture is smooth the values of the matrices will be more spread out [7]. In this paper, four of the most commonly used descriptors (homogeneity, contrast, ASM and entropy) are used to extract textural features from the 20 GLCM of the ultrasonic texture image data set. The parameters are computed according to the follow formulas:

Homogeneity: $Hom = \sum_{g_1} \sum_{g_2} \frac{p(g_1, g_2)}{1 + (g_1 - g_2)^2}$ (9)

Contrast: $CON = \sum_k k^2 \left[\sum_{g_1} \sum_{g_2} p(g_1, g_2) \right]$ (10)

$$k = |g_1 - g_2|$$

Angular Second Moment:

$$ASM = \sum_{g_1} \sum_{g_2} [p(g_1, g_2)]^2 \quad (11)$$

Entropy:

$$ENT = -\sum_{g_1} \sum_{g_2} p(g_1, g_2) \log_2 p(g_1, g_2) \quad (12)$$

Where $P(g_1, g_2)$ is the appearance probability of the gray of two pixels (g_1, g_2). Each measurement is evaluated for $d = 2$, and θ =0°, 45°, 90° and 135°.

D. Texture Clasification Based on PNN

Neural network is usually employed in pattern recognition owing to its great potential for parallel processing and based on learning from examples. Back Propagation Neural Network (BPNN) is of low convergence speed and susceptibility to the local minimum. The Probabilistic Neural Network (PNN) can avoid these shortcomings. The PNN develops from radial-basis-function neural network (RBFNN) and approaches the Bayes theorem maximum posterior probability [8], thus it is employed as a classifier in our method.

III. EXPERIMENTS

The normal and fatty images are shown in Fig. 1. Firstly image preprocessing should be done by image De-noising [9]. Then region of interest (ROI) of each ultrasonic liver image is processed with the above three methods.

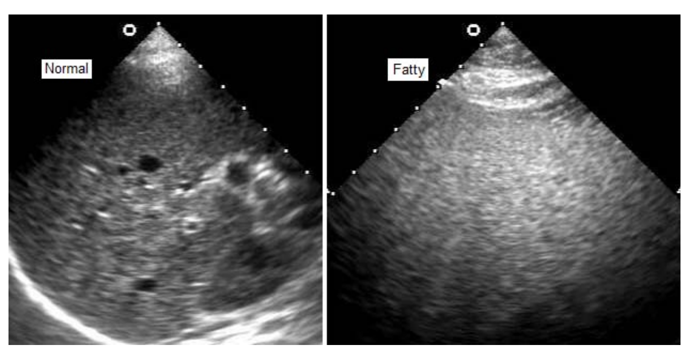

Figure 1. Normal and fatty ultrasonci image

A. Experiments on Gray Level Histogram

Parameters extraction based on gray level histogram are disposed respectively to ten normal liver images and ten fatty liver images, data record as shown in Fig. 2. Real line indicates fatty liver and dashed line is normal.

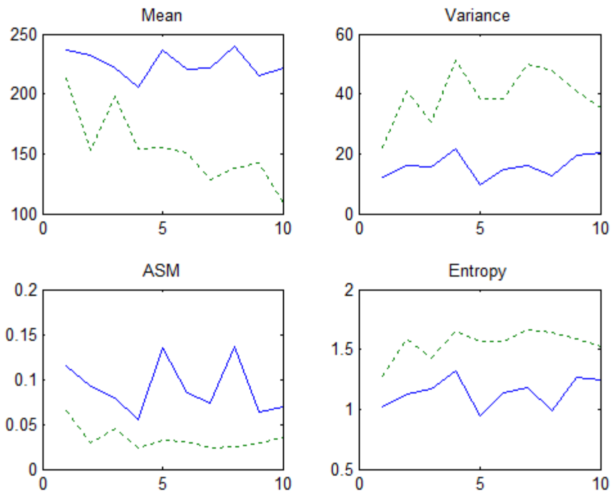

Figure 2. Feature parameters derived from gray histogram

B. Experiments on GLDS Method

Parameters extraction based on GLDS are disposed respectively to ten normal liver images and ten fatty liver images, data record as shown in Fig. 3. Real line indicates fatty liver and dashed line is normal.

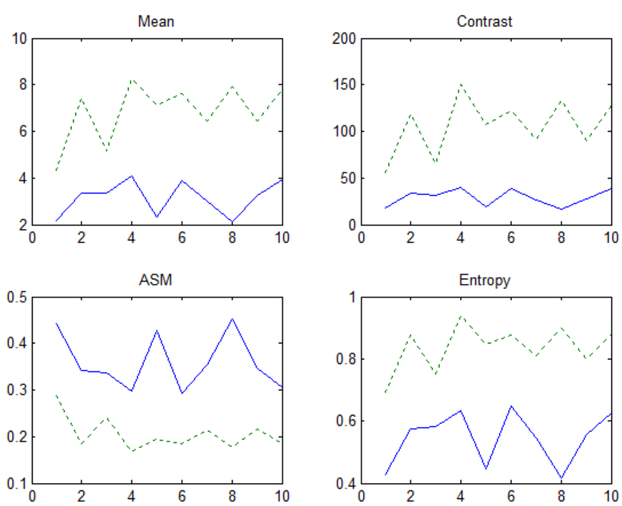

Figure 3. Feature parameters derived from GLDS

C. Experiments on GLCM Method

Firstly GLCM of ROI must be obtained, as shown in Fig. 4-5, which shows that GLCM elements of fatty liver distribute intensively (Fig. 4) and elements of normal liver distribution are relatively dispersed (Fig. 5). In order to make out the difference, characteristic parameters based on GLCM are calculated out in accordance with respective GLCM. Data record is shown in Fig. 6, real line indicates fatty liver and dashed line is normal.

The mean of four directions (0°, 45°, 90°, and 135°) parameters is used as image feature parameter. For example, *ASM = (ASM1+ASM2+ASM3+ASM4)*/4, in the same way, calculation methods of Hom, CON and ENT is similar.

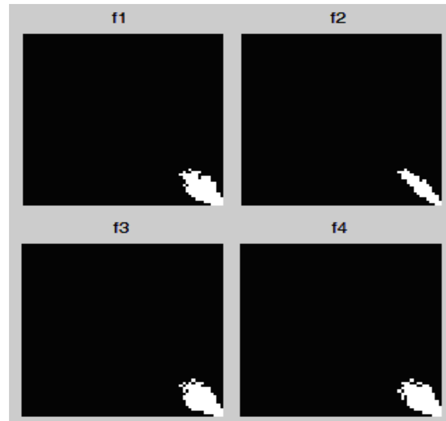

Figure 4. The 4 directions($\theta=0°,90°,45°,135°$) GLCM of fatty

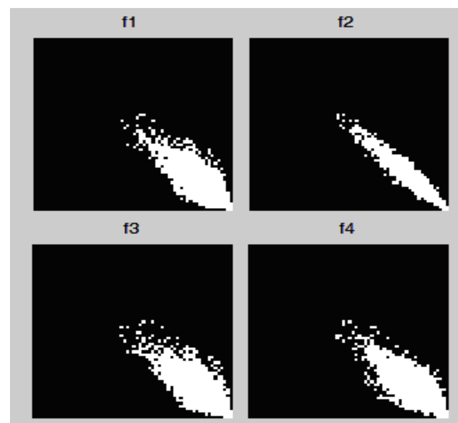

Figure 5. The 4 directions($\theta=0°,90°,45°,135°$) GLCM of Normal

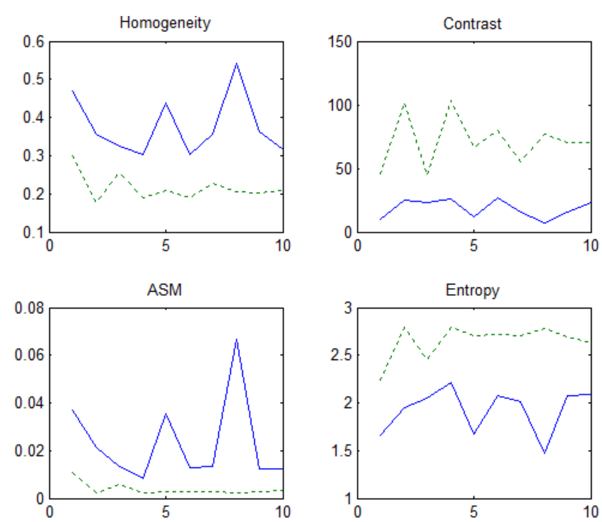

Figure 6. Feature parameters derived from GLCM

From the data record as shown in Fig. 2, we can concluded that the value of Mean of fatty image from gray histogram is bigger than that of the normal, which indicates that the echo intensity of fatty image is stronger than that of the normal, in fact it is true according to the visual effect of the vision and the pathological change.

From the data record as shown in Fig. 3, the value of Mean of fatty image from GLDS is smaller than that of the normal, which indicated that the gray level of fatty image is comparatively even and have little change.

The values of ASM from the three methods of fatty image are bigger than that of the normal; and the values of Variance, Contrast and Entropy of normal are bigger than that of the fatty, which indicates that the texture mode of fatty image is more uniform and compacted, while the texture of normal image contains more high frequency components and the texture is rougher.

Five characteristic parameters were selected from the above twelve parameters. The 5 parameters, including Variance from gray histogram, Mean and Contrast from GLDS and Contrast and Entropy from GLCM, constitute a feature vector as the input of neural network to make automatic classification and recognition.

D. Experiments on Texture Classification by PNN

In our research work, fifty normal ultrasonic images and fifty fatty ultrasonic images are selected for feature parameters extracted and pattern recognition. Eighty sample ultrasonic images are taken out as learning sample to training neural network; another twenty images are taken out as testing sample. Five parameters extracted from every sample constitute a feature vector, i.e. 5-dimension vector as the input of PNN to make automatic classification and recognition. Recognition rates of fatty liver and normal liver are above 87.5% and 82.5% separately as shown in table I.

TABLE I. CORRECT CLASSIFICATION RATE OF PNN BY DIFFERENT METHOD

	Normal image	Fatty image
Gray level Histogram	75%	72.5%
GLDS	80%	85%
GLCM	82.5%	85%
5 Joint Parameters	85%	87.25%

IV. CONCLUTION

Ultrasonic normal liver image and ultrasonic fatty liver image have different granular which could be described by texture feature such as Mean, Variance, Contrast, ASM and Entropy. The effects of feature extraction are determined by image De-noising, pathological change and the algorithm. Texture analysis could be performed by applying more efficient algorithms and larger data set used for testing. Feature extraction, feature parameters selected and texture classification are always focus and difficulty in image processing, because there is no unified standard and method. The algorithm presented in this paper could be applied to texture analysis in other liver disease ultrasonic image such as hepatitis and cirrhosis.

The extracted quantization feature parameters could improve ultrasonic detection rate. It is auxiliary to doctor in diagnosis of patients according to ultrasonic images.

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