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Quantitative grading diagnosis system of fatty liver for b-ultrasonic image

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Abstract. This article research content is a quantitative grading diagnosis system of fatty liver for B-ultrasonic image. We analyze a lot of characteristics and construct some new features, such as Near Far Field Intensity Ratio (NFFIR), Near Far Field Intensity Variance Ratio (NF-FIVR), near field Speckle Number (SN) and near field Speckle Size (SS). After that we use receiver operating characteristic curve (ROC) analyze the feature effectiveness including near far field gray level based features, histogram based features, Gray Level Co-occurrence Matrix (GLCM) based features, Neighborhood Gray-Tone Difference Matrix (NGTDM) based features and Near Field Echo Intensity based features. By using BP neural network to the training sample data, and using leave one out method to select feature vector and evaluating, we find the features combination citation{ NFFIR + NFFIVR + CON (GLCM) + COS (NGTDM) + SN } is one of the best combination, and this combination achieves the highest recognition rate. Experimental results show that the system can fairly precisely auxiliary diagnosis of four magnitude, including normal liver, mild fatty liver, moderate fatty liver and severe fatty liver.

Key words. B-ultrasonic image, quantitative grading, diagnosis system, fatty liver, field Intensity.

1. Introduction

As a much more mature technology, ultrasound imaging has been widely used in the fatty liver diagnosis.However, due to various factors, clinical doctors often show some subjectivity and limitations of empirical judgment, which will affect the diagnosis result to some extent [1-3].

Using the computer for calculation and analysis of the illness, by which, auxiliary

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diagnosis results reflect the image information objectively [4]. Ultrasonic diagnosis and classification of fatty liver mainly rely on the doctor's subjective experience and quantitative. The objective quantitative standard has not been formed, which is also prone to the main reasons of misdiagnosis [5].

The purpose of this paper is to explore how to use the powerful ability of the grading system to calculate the statistics texture feature of liver ultrasound image, and provides the reliable clinical auxiliary diagnosis. At the same time, we want to maximize the potential of ultrasonic image based examination, to discover the liver disease as soon as possible. The system can also be used on routine inspection of the liver, and prevent a lot of kinds of liver disease effectively.

2. Feature extraction

2.1. The characteristics based on near far field gray level

Fatty liver patients with hepatic fatty infiltration resulted in large amount of the ultrasonic absorption and scattering. The ultrasonic images reflect is the echo enhancement, liver area dot uniform densely, and diffuse fine dot echoes, the first half of the liver spectral brightness enhanced, coarser, commonly known as "bright" liver. This means that the image average gray level and nearly field and far field variance are two characteristics of fatty liver disease severity, which have better description ability fore recognition and quantitative .

2.1.1. Near Far Field Intensity Ratio (NFFIR)

Taking the Near field ROI Intensity Sum as formula $IS = \sum_{x=0}^{W-1} I_{near}$ (1)

Where, H and W, respectively represent the height and width of ROI, $I_{near}(x,y)$ is the near field grey value in the ROI. The gray sum of the far field ROI

$$IS_{far} = \sum_{y=0}^{H-1} \sum_{x=0}^{W-1} I_{far}(x,y) \tag{1}$$

So we get the Near Far Field Intensity Ratio

$$NFFIR = IS_{near}/IS_{far} \tag{2}$$

2.1.2. Near Far Field Intensity Variance Ratio (NFFIVR)

Assume the near field Intensity Variance

$$IV_{near} = (\sum_{y=0}^{H-1} \sum_{x=0}^{W-1} (I_{near}(x,y) - M_{near})^2)^{\frac{1}{2}} \tag{3}$$

the far field Intensity Variance $IV_{far} = (\sum_{y=0}^{H-1} \sum_{x=0}^{W-1} (I_{far}(x,y) - M_{far})^2)^{\frac{1}{2}}$ (5)
then the Near Far Field Intensity Variance Ratio can be express as

$$NFFIVR = IV_{near}/IV_{far} \tag{4}$$

2.2. The characteristic based on histogram

Histograms reflect in the image grayscale and appear this kind of gray level of the relationship between the probabilities of graphics. Make statistical analysis on unit area of pixels, using two-dimensional coordinate chart can display the results in the form of order, gradually increases from left to right, ordinate said a grey value of pixels as a percentage of the region.

2.2.1. Skewness (S)

The Skewness is to reflect the histogram of symmetry, if the value is positive, it means histogram right distribution, and conversely for distribution to the left.

$$S = \frac{1}{V_{near}^3} \sum_{r=0}^{L-1} (r - M_{near})^3 p(r) \tag{5}$$

Where, V_{near} is the near field gray standard deviation of the ROI, $M_{near}$is the near field grayscale average of ROI, *p(r)* is the near field of grayscale frequency with r in ROI.

2.2.2. First-percentile Grey Level (FGL)

$$\sum_{j=0}^{P_1-1} h_j < \frac{1}{10} \leq \sum_{i=0}^{P_1} h_i \tag{6}$$

So-called of FGL, i.e., less than the number of pixels of grayscale P1 accounted for 10% of the total number of pixels.

2.3. The characteristic based on Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) is a kind of texture method with wide application, which not only contains the gray level statistics, but also reflects the image grayscale on direction, adjacent interval and amplitude change information. It is based on a grayscale structure in the texture repeated. This structure in the fine texture with distance and quick change, while in the rough texture change slowly.

How frequencies appeared in the ROI of point (x_1, y_1) with gray i and point(x_2, y_2) with gray j in the direction of θ spacing as d, can be used to formulate by a joint probability density function $p(i, j|d, \theta)$

$$p(i, j|d, \theta) = \#\{f(x_1, y_1) = i, f(x_2, y_2) = j\} \tag{7}$$

2.3.1. Angular Second Moment (ASM)

Angular second moment is one of measurements of the image texture thickness. When image texture is meticulous, and gray values distribute uniformly, the ASM value is big, on the other hand, when the image grey distribution is very uneven, and rough enough, ASM value is small accordingly.

$$ASM = \sum_{i,j=0}^{L-1} p(i,j)^2 \tag{8}$$

chsdate Year 1899 Month 12 Day 30 IsLunar Date False Is ROC Date False

2.3.2. Entropy (ENT)

Entropy is the measure of the amount of image information. Entropy shows the heterogeneous and complex degree of image texture. Entropy is big, shows that complex degree is high; on the contrary, entropy is small shows low complex degree.

$$ENT = \sum_{i,j=0}^{L-1} P_{i,j}(-\ln p_{i,j}) \tag{9}$$

2.3.3. Inverse Differential Moment (IDM)

Inverse difference moment reflects the regular extent of image texture. When grain desultorily, inverse difference moment is lesser, on the contrary, inverse difference moment is bigger.

$$IDM = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{p_{i,j}}{1+(i-j)^2} \tag{10}$$

2.3.4. Contrast (CON)

Evenness reflects the grayscale distribution uniformity, texture image texture distribution is more homogeneous, the greater the value of HOM is, on the contrary, the smaller the evenness is.

$$HOM = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{P(i,j)}{1+|i-j|} \tag{11}$$

2.4. The characteristic based on Neighborhood Gray-Tone Difference Matrix

Neighborhood Gray-Tone Difference Matrix (NGTDM) is a kind of measuring approach to the texture attributes. It makes the machine vision with the human senses are well corresponding in texture analysis.

NGTDM calculation process is as follows. Assume I(x,y) is the pixel grey value with coordinate (x,y), then we have the average grey value

$$\overline{A}(x,y) = \frac{1}{w^2-1}\left[\sum_{m=-d}^{d}\sum_{n=-d}^{d} I(x+m,y+n)\right] \tag{12}$$

where$(m,n) \neq (0,0)$, w=(2d+1)^2.

The i-th item is

$$S(i) = \sum \left| i - \overline{A}(x, y) \right| \tag{13}$$

2.4.1 Coarseness (COS)

$$COS = [\varepsilon + \sum_{i=0}^{G_h} p_i S(i)]^{-1} \tag{14}$$

2.4.2 Contrast (CON)

$$CON = [\frac{1}{N_g(N_g - 1)} \sum_{i=0}^{G_h} \sum_{j=0}^{G_h} p_i p_j (i - j)^2][\frac{1}{n^2} \sum_{i=0}^{L-1} s(i)] \tag{15}$$

2.4.3 Busyness (BUS)

$$BUS = \frac{\left[\sum_{i=0}^{G_h} p_i s(i)\right]}{\left[\sum_{i=0}^{G_h} \sum_{j=0}^{G_h} ip_i - jp_j\right]} \tag{16}$$

2.4.4 Complexity (COM)

$$COM = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} \{(|i - j|)/(n^2(p_i + p_j))\}\{p_i s(i) + p_j s(j)\} \tag{17}$$

2.5. The characteristic based on Near Field Echo Intensity

Statistics of the number of dot area in ROI can be used as a measure of fatty liver in Near Field liver characteristics, which reflect the Near Field Echo Intensity (NFEI).

Step1, using LoG convolution with near-field ROI areas, the template is

$$\begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & -1 & -2 & -1 & 0 \\ -1 & -2 & 16 & -2 & -1 \\ 0 & -1 & -2 & -1 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix}.$$

Step2, the above results are binary segmented by using the method of single threshold segmentation, $g(x, y) = \begin{cases} 255 & f(x, y) > T \\ 0 & f(x, y) < T \end{cases}$ (21)

After that, we can count the Speckle Number and calculate the Speckle Size as the characteristic.

2.5.1 Speckle Number (SN)

SN = number {Speckle size > Threshold} (22)

2.5.2 Speckle Size (SS)

SS = $\sum Speckle$ / SN (23)

3. The quantitative grading diagnosis system flow

The process of the quantitative analysis mainly includes: ROI extraction, feature extraction, classifier training and recognition. Fatty liver ultrasound quantitative system is shown in figure. Doctor training is equivalent to accumulate experience in clinical diagnosis. In the classifier training, a set of tags real disease in the ultrasound images (usually given by the doctor) are sent to extract the feature parameters, the optimal characteristic vector space are sent into the classifier to formulate the training parameters.

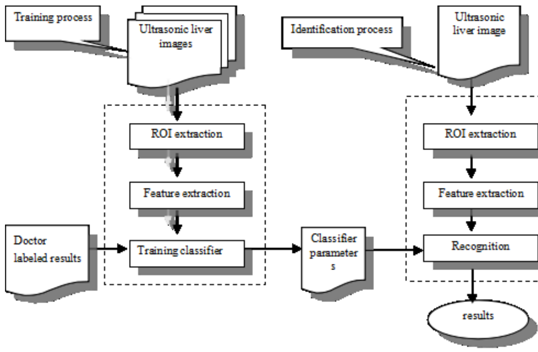


Fig. 1. The design process of the quantitative analysis of fatty liver ultrasound imag

4. Receiver operating characteristic curve analysis

Receiver Operating Characteristic (ROC) Curve analysis has been widely applied in the evaluation of medical diagnostic test. Real positive (mass) cases and the actual negative (normal) distribution of the two cases may overlap. At this time we can use the ROC curve analysis methods to quantify the separability of two distributions. Given a threshold, a side makes a positive decision, on the other side to do the negative decision. Define the true positive fraction (TPF) and the false positive fraction (FPF) as follows

$$TPF = \frac{the\ number\ of\ ture\ positive\ and\ made\ a\ positive\ decision}{the\ number\ of\ ture\ positive} \tag{18}$$

$$FPF = \frac{the\ number\ of\ false\ positive\ but\ made\ a\ positive\ decision}{the\ number\ of\ false\ positive} \tag{19}$$

Where, $TPF = \int_T^\infty f(x)dx$ and $FPF = \int_T^\infty g(x)dx$, f is the positive cases distribution probability density function, and g is the negative cases distribution probability density function.

5. Experimentations and results

By using the feature selection methods, we get the combined feature selection results including {NFFIR + NFFIVR + CON (GLCM) + COS (NGTDM) + SN}, {NFFIR + NFFIVR + FGL+ BUS (NGTDM) + SN + SS}, {S + ASM (GLCM) + HOM (GLCM) + COM (NGTDM) + SS}, {IDM (NGTDM) + BUS (GLCM) + COM (GLCM) + SN}, and {NFFIVR + FGL + ENT (GLCM) + COS (NGTDM) + SS + SN}.

Table 1. ROC curve and Az values of several effective features for different level classification

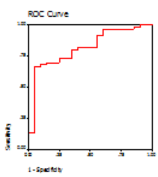
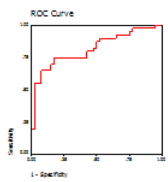
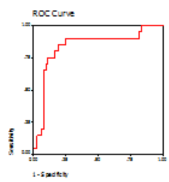
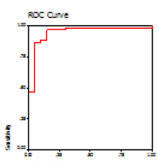
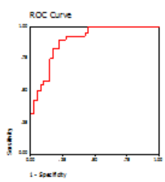
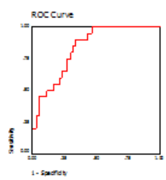
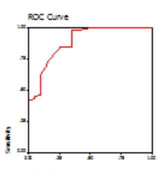
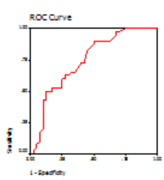
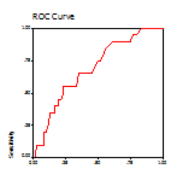
	Normal - mild & moderate & severe	**Normal & mild - moderate & severe**	**Normal & mild & moderate - severe**
Near Far Field Intensity Variance Ratio	 Az = 0.817	 Az = 0.818	 Az = 0.832
Near Far Field Intensity Ratio	 Az = 0.944	 Az = 0.891	 Az = 0.833
Speckle Number	 Az = 0.889	 Az = 0.742	 Az = 0.686

Table 2. Combined feature selection results

Combined feature	**Recognition rate**			
	Normal	**Mild**	**Moderate**	**Severe**
NFFIR + NFFIVR + CON (GLCM) + COS (NGTDM) + SN	95%	90%	95%	85%
NFFIR + NFFIVR + FGL+ BUS (NGTDM) + SN + SS	90%	90%	80%	80%
S + ASM (GLCM) + HOM (GLCM) + COM (NGTDM) + SS	65%	75%	70%	55%
IDM (NGTDM) + BUS (GLCM) + COM (GLCM) + SN	70%	60%	65%	80%
NFFIVR + FGL + ENT (GLCM) + COS (NGTDM) + SS + SN	85%	85%	75%	85%

6. conclusion

We use The BP neural network classifier and leave one out method to evaluation the system. According to the identification results in the table, we can find features combination {NFFIR + NFFIVR + CON (GLCM) + COS (NGTDM) + SN} is one of the best combinations, and we use this combination to achieve the highest recognition rate. Therefore, the fatty liver ultrasound image quantitative grading diagnosis system can be applied to clinical auxiliary diagnosis.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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