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Fatty Liver Recognition Based on Computer Vision

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Abstract: Current clinical method often uses B-ultrasound for the diagnosis of fatty liver, which basically rely on the doctor observation. Therefore, automatic recognition of fatty liver from the B-ultrasound images has significance value of clinical application. According to the characteristics of fatty liver in B-ultrasound images, this paper proposed five useful features to formulate the new feature vector, which include the near-field echo density, the average gray ratio from the near to far field, as well as three texture features from the gray level co-occurrence matrix and the neighborhood gray-tone difference matrix such as angle second moment, entropy and busyness. These features are chosen carefully, which have good characteristic for distinguishing fatty liver. Based on the support vector machine classification of these feature vectors, the experiments show that the proposed method achieves a good recognition rate of normal liver and fatty liver, which is 91.7% and 98.7% respectively. Compare with the previous work, our experimental data is much more abundant, and the recognition rate is higher as well. Furthermore, with the proposed method, the reader could obtain fatty liver classifier easily.

Key words: Ultrasound images, feature vector, fatty liver, support vector machine

INTRODUCTION

Fatty liver is the disease which results from the excessive accumulation of fat in the liver cells. If we do not control fatty liver without delay, the disease may cause hepatitis, cirrhosis of the liver, which will result in permanent damage to the liver.

At present, the cases with fatty liver is increasing in the global scope. Due to obesity, alcoholism and diabetes, fatty liver has become the second hepatitis liver disease.

For clinical diagnosis of fatty liver, biopsy is the "gold standard". However, liver biopsy is invasive, and patients are often reluctant to accept the diagnosis of this kind. With the rapid development of medical ultrasound, current clinical method often uses B-ultrasound imaging techniques in the diagnosis of fatty liver, but these diagnoses basically stay in the doctor observation to check whether subjects suffer from fatty liver and to diagnosis the severity of fatty liver.

These artificial methods mainly rely on subjective experiences of doctors and non quantifiable descriptions. Furthermore, doctors have not yet formed a quantitative standard for fatty liver diagnosis by ultrasound. This is also the main reason of misdiagnosis. Therefore, taking advantage of the quantitative analysis using medical knowledge and image processing technology, automatic recognition of fatty liver has significance value of clinical application.

With the development of image processing and pattern recognition, auxiliary diagnosis of hepatic disease by computer has made some progress. Some research results show that, Characteristics of ultrasound images, such as the gray histogram (Linares *et al*, 2003), the gray level co-occurrence matrix (Yeh *et al*, 2003), TFCM (Ming-Huwi Horng *et al*., 2002; Ming-Huwi Horng *et al*., 1998) and adjacent point operator (Chung-Ming Wu *et al*., 1992), can be used to identify liver disease.

Considering the characteristics of fatty liver performed in B-ultrasound images, this paper extracts the characteristics of the near-field echo density, the average gray ratio from the near to far field, as well as the texture features from the gray level co-occurrence matrix and the gray level difference matrix. We select the most effective features from them to form the best feature vector in fatty liver analysis of B-ultrasound image. Based on the support vector machine classification of feature vectors, we achieve the objective for distinction between normal liver and fatty liver finally.

FEATURE EXTACTION

Fatty liver in ultrasound image usually performs as follows:

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- The spots are fine and dense,
- The near field echo enhances obviously,
- The far field echo attenuates with different degree.

By synthesizing the comprehensive features of fatty liver image in texture characteristics, we carried out the studies on the extraction method of describing the liver B-ultrasound image features.

From a lot of experiments, we found that the five features is more suitable for establishing the optimal feature vector in fatty liver B-ultrasound image analysis, which includes near field echo density, intensity ratio from near field to far field, Angular second moment and entropy of the gray level co-occurrence matrix, as well as finesse of the local gray level difference matrix. So this paper uses these five features for the recognition of fatty liver in B-ultrasound images.

In order to calculate the five features mention above, we need to select a region of interest (ROI) in the B-ultrasound image. In the experiments, the selection of ROI should obey the following principles:

- Each image extracts two ROIs, one is located in the near field, another is located in the far field;
- The size of the region of ROI is fixed as 64 x 64 pixels;
- The ROI selection should avoid vascular and shadow interference of texture analysis;

A typical example of the ROI selection is shown in Fig. 1.

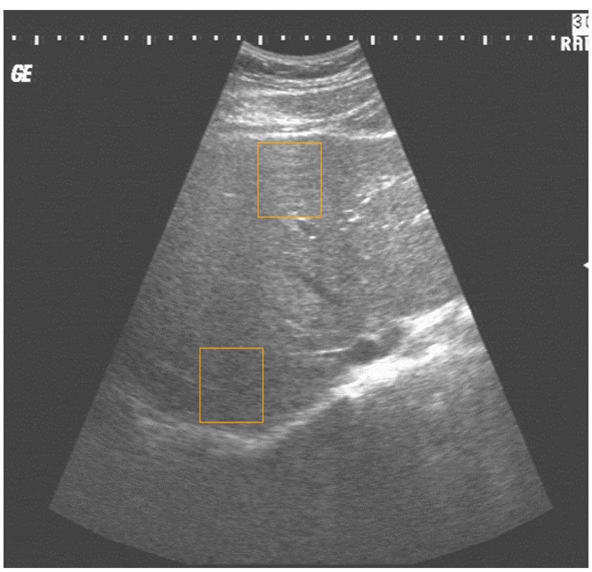

Fig. 1: A typical example of the ROI selection (The upper region is near field, the lower region is far field)

THE NEAR FIELD ECHO DENSITY

The B-ultrasound image performance of fatty liver for the near field is the spot density and brightness increasing obviously, which will cause the pixel neighboring region gradient increasing. Therefore, quantitative the number of spots with gradient increasing as the density characteristics of ultrasonic liver image is very effective (Fig. 2).

Statistical methods for the number of spots are as follows:

- Processing the near field ROI regions by using LoG operator, the LoG operator is used in a 5 x 5 templates as following.

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

- Deciding according to the threshold. Each pixel in ROI area, if the gradient is less than a threshold, then the value is set to 0, otherwise set to 255.
- Statistics non-connected region number with value 255 in ROI region after binaryzation.

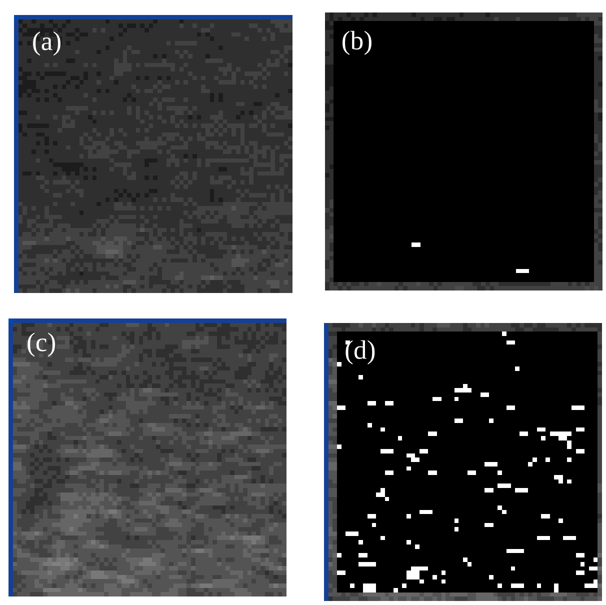

Fig. 2: (a) Normal liver ROI, (b) After LoG operation and binaryzation from (a), (c) Fatty liver ROI, (d) After LoG operation and binaryzation from (c)

THE MEAN INTENSITY RATIO FROM NEAR FIELD TO FAR FIELD

The accumulated fat in the liver of patients with fatty liver will lead to A lot of absorption and scattering of ultrasonic, where the image shows the near field echo of liver parenchyma brightening and the far field echo attenuation. Therefore, fatty liver and normal liver B-ultrasound images are different in the near and far field intensity ratio.

The near field ROI gray (Intensity Sum) is expressed as the sum of:

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

Where H and W is the height and width of the ROI respectively ; x and y is the pixel coordinate; $I_{near}(x,y)$ is the pixel gray values in the near field ROI.

The far field ROI gray (Intensity Sum) is expressed as the sum of:

$$IS_{far} = \sum_{y=0}^{H-1}\sum_{x=0}^{W-1} I_{far}(x,y) \tag{2}$$

Where $I_{far}(x,y)$ is the pixel gray values in the far field ROI.

The near and far field intensity ratio (Intensity Sum Ratio, ISR) is defined as:

$$ISR = IS_{near} / Is_{far} \tag{3}$$

GRAY LEVEL CO-OCCURRENCE MATRIX

The organizational structure of fatty liver will be damaged, so the texture features will be changed in B-ultrasound image. The gray level co occurrence matrix (GLCM) has been theoretically proved that is a good method in texture analysis (Haralick *et al*, 1973). Experiments show that angular second moment and entropy of the gray level co-occurrence matrix has a good performance in separating normal liver and fatty liver image.

GLCM is a matrix function of pixel distance and angle. $N_{d\theta}$ (i,j) represents the number of pixel pair whose gray values are i and j, the distance is d, and the the horizontal angle is θ.

After normalizing $N_{d\theta}$ (i,j), we get the probability of the pixel pair as follows.

$$p(i,j|d,\theta) = \frac{N_{d,\theta}(i,j)}{N} \tag{4}$$

Where N is the total number of pixel pair. The GLCM features which have good ability to describe the liver B-ultrasound image texture is angular second moment and entropy.

a) angular second moment

$$asm = \sum_{i,j=0}^{L-1} p(i,j)^2 \tag{5}$$

Where L is the gray level of the image.

b) entropy

$$ent = \sum_{i,j=0}^{L-1} P_{i,j}(-\ln p_{i,j}) \tag{6}$$

NEIGHBORHOOD GRAY-TONE DIFFERENCE MATRIX

Neighborhood gray-tone difference matrix (NGTDM) has good correspondence for the machine vision and human sense in texture analysis (Amadasun *and King,* 1989). NGTDM reflects the gray difference from pixel with some gray value and neighborhood pixels. Experiments show that the frequency of NGTDM (busyness) can be used as a discriminating feature of fatty liver.

We assume the ROI image is I(x,y) and the window size is W×W, where W = 2d+1 (d is set as 1 or 2), the mean matrix is as follows.

$$\overline{A}(x,y) = \frac{1}{w^2-1}\left[\sum_{m=-d}^{d}\sum_{n=-d}^{d} I(x+m, y+n)\right] \quad (x,y)\neq(0,0) \tag{7}$$

Then get the sequence S (i), where S (i) represents The sum of absolute value of the difference from all pixels with gray value as i to the corresponding mean matrix $\overline{A}$ (x,y).

$$s(i) \sum | i - \overline{A}(x,y) | \quad I(x,y) = i \tag{8}$$

The busyness is defined as follows.

$$f_{bus} = \left[\sum_{i=0}^{G_h} p_i s(i)\right] \Big/ \left[\sum_{i=0}^{G_h}\sum_{j=0}^{G_h} ip_i - jp_j\right] \quad p_i \neq 0,\ p_j \neq 0 \tag{9}$$

SVM CLASSIFICATION

Support vector machine (SVM) is a new method of pattern recognition formed on the basis of statistical

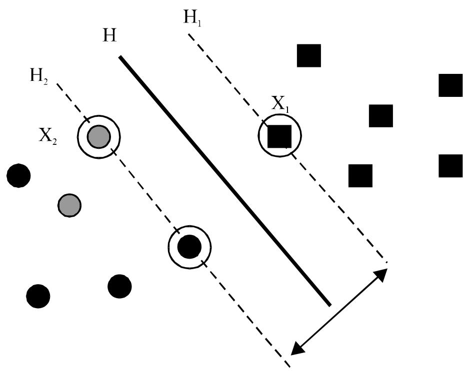

Fig. 3: The optimal hyperplane

learning theory (Vapnik, 2000 transforms the solving problem of pattern recognition into a quadratic programming optimization problem, which ensures the global optimal solution theoretically, avoiding local convergence. SVM is currently one of the best methods for small sample estimation and prediction learning. In our experiments, we use support vector machine classifier on the diagnosis of fatty liver, which achieves a high recognition rate. The basic principle of support vector machine is to find an optimal hyperplane, and maximum classification clearance on both sides. Figure 3 shows the optimal hyperplane in feature space in a given training data set of two valued classification problems. Where, solid circles and solid squares represent two kinds of samples, and the middle interface H represents the optimal classification face.

When the problem is not separable, linear classification problem could be transformed into another space by a nonlinear transformation to find the optimal classification face. The nonlinear transform is defined by the appropriate kernel function. The selection of kernel function is very important to improve the classification performance and generalization ability, usually using polynomial kernel function, RBF kernel function. In view of the excellent nonlinear classification properties of RBF kernel function, we adopt the RBF kernel as the kernel SVM classifier.

The selected radial basis function kernel is represented as follows.

$$K(x, x_i) = \exp\{-\gamma |x - x_i|^2\} \tag{10}$$

EXPERIMENTAL RESULTS AND DISCUSSION

In our experiments, 99 subjects B-ultrasound images were used for studying, the normal liver image number is 24, while the fatty liver image number is 75. We use the GE B-ultrasound as the data acquisition machine. The ultrasonic probe transmitting frequency and receiving frequency is 4MHz.

Table 1: The recognition rate of normal liver and fatty liver

Catalogue (%)	Sample number	Recognition rate
Normal liver	24	91.7%
Fatty liver	75	98.7%

According to the doctor's experience, we choose ROI from each B-ultrasound image to analysis and calculate. While calculate the near field echo density, the binaryzation threshold of gradient value is set as 200. For the angular second moment and entropy of the gray level co-occurrence matrix, the gray level 256 is binned by 16, the parameter d=1, and $\theta = 0°$, when calculate the busyness of NGDTM, the window size is set as 5×5. We use the leave one out method to calculate the recognition rate. That is to say we use 98 samples for training the SVM classifier, and use the left one sample for recognition. The result show our method have a good performance in recognizing normal liver and fatty liver.

The references of fatty liver ultrasonic image quantitative classification are less in the worldwide, especially; we need the gold standard database with different degrees of fatty liver cases data for liver ultrasonic image testing.

Although the recognition rate in literature (P.A.Linares *et al*, 2003) is good, most of the experimental data of the using fatty liver are moderate and severe fatty liver, which were 9 cases and 3 cases. Compare with that, our experimental data is much more abundant, moderate and severe fatty liver is 5 cases each, the left 65 cases are mild fatty Liver, so the result of the experiment is more reliable, and our recognition rate is higher as well.

From the experimentations, we found that while Fatty liver ultrasonic reflection and scattering area increase, texture become thicker, so the angle second moment becomes small. Entropy is used to measure the degree of confusion in the image; fatty liver image texture is more complexity and chaos than normal liver image, so the entropy is smaller. Frequency reflects the difference between pixel and the neighborhood, so these texture parameters was significant good also. The results show the classifier is effective in recognizing fatty live.

CONCLUSION

According to the characteristics of ultrasound images, we extract feature vector composed of 5 characteristics, and then use the support vector machine classification to realize the recognition of normal liver and fatty liver. The method proposed in this paper can help doctors to diagnose fatty liver by the computer image automatic analysis and classification. The misdiagnosis could fall to the lowest in the doctor diagnosis process due to subjective differences caused by the doctors. On the other hand, the automation computer aided diagnose will greatly improve the efficiency of clinic diagnosis of fatty liver.

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