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Improving the Classification of Cirrhotic Liver by using Texture Features

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***Abstract*—We have been developing a computer-aided diagnosis (CAD) system for distinguishing the cirrhosis in MR images by shape and texture analysis. Two shape features are calculated from a segmented liver region, and seven texture features are quantified by using grey level difference method (GLDM) within the small region-of-interests (ROIs). The degree of cirrhosis is derived from integrating the shape and texture features of the liver into a three-layer feed-forward artificial neural network (ANN). A liver is regarded as cirrhosis if the percentage of the ROIs with a degree over 0.5 is greater than 50%. The initial experimental result showed that the ANN can learn all of the patterns in the training data sets. In testing of the whole liver regions, 82% cirrhosis and 100% normal cases were correctly differentiated from 18 test cases, that indicates our proposed method is effective to the cirrhosis prediction on MRI.**

I. Introduction

Cirrhosis of the liver is a late stage of progressive liver disease defined as structural distortion of entire liver by fibrosis and parenchymal nodules. As the cirrhosis may increase the risk of hepatocellular carcinoma, early detection and accurate staging of cirrhosis is an important issue in practical radiology. Although there is no effective treatment for decompensate or advanced cirrhosis, interferon therapy is sometimes beneficial for early cirrhosis associated with viral hepatitis [1]. Therefore, early diagnosis is critical in cirrhosis to establish the cause of the disease and to determine the amount of existing liver damage that may help determine proper treatment in patients with this disease. The diagnosis of cirrhosis is carried out by physical inspections, serological tests, radiologic imaging, liver biopsy, or a combination. Recently, although the magnetic resonance imaging [MRI] is widely used for the diagnosis of the liver, information obtained from MRI is of quite a variety, and it is difficult for inexperienced radiologists or physicians to interpret MR images of the liver. Cirrhosis may cause structural distortion of entire liver by fibrosis and parenchymal nodules. These image findings in MR images can be interpreted by shape and texture analysis. However, such procedure is often subjective in clinical practice. Our purpose is to establish a computer-aided diagnosis (CAD) system for quantifying the analysis and providing decision aid in diagnosis of cirrhosis on MR images.

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II. Materials And Method

A. Review Stage

As the liver parenchyma regenerate after hepatocyte necrosis, fibrosis of a variety of degree develops throughout the liver and cause gross distortion in configuration to the liver [2, 3]. Some efforts have been done by investigating hepatic morphologic changes on imaging, such as CT, MRI and ultrasonography. McNeal et al. [4] investigated a method for measuring the volumes of human livers in vivo from MRI and subsequently displaying these livers in three dimensions. His result indicates that the changes in liver volume predicts the prognosis of patients with cirrhosis, but cirrhotic livers only slightly reduce in size compared with healthy livers and the whole liver volume could not provide significant value in the diagnosis of cirrhosis. Awaya et al. [5] measured caudate-right lobe (C/RL) ratio with use of the right portal vein to overcome the above mentioned problem. We also propose a novel method to quantitatively calculate the degree of cirrhosis based on the hepatic volume ratio of left-to-whole [6]. However, the diagnostic accuracy is not yet satisfied due to the result only from analyzing the shape feature of liver. Wang et al. [7] used texture analysis with the co-occurrence matrix method to analyze ultrasonograms from normal and diseased livers, and X-ray CT images obtained from normal cases and cases of idiopathic interstitial pneumonia. Although the different pathological grades of fibrosis and the different size of nodules in the cirrhotic and normal liver groups had different Fisher ratios, the normal and diseased liver groups could not differ significantly. In this paper, we try to combine the texture features into our previous shape analysis based CAD system, and investigate if the fibrosis changed in liver

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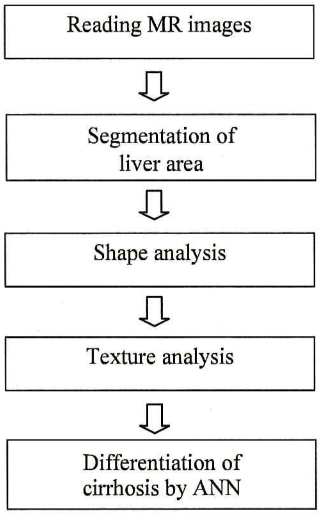

Fig.1 Overall flowchart of our scheme for an automated differentiation of cirrhosis in MR images.

on MRI is useful to the classification of cirrhosis.

B. Overall strategy and methods

Marginal dullness, surface irregularity, atrophy of quadrate lobe and right lobe, fibrosis and regenerative nodule as well as the swelling of caudate lobe and lateral segment of left lobe are helpful signs at MR imaging in diagnosis of cirrhosis of the liver. Our experiment is focused on the marginal dullness and the regenerative nodules and fibrosis.

The overall flowchart of our CAD scheme is shown in Fig.1: a 2D MR slice containing the main portal vein inside is selected firstly, then the liver region is segmented by our program [6]. Shape analysis calculates the features of marginal dullness on left lobe of liver, and texture analysis calculates the features of regenerative nodules and fibrosis. Finally the degree of cirrhosis is given by the output of an artificial neural network (ANN).

C. Shape analysis of the Liver

In order to calculate the dullness of lateral segment of left hepatic lobe, two approximated straight lines a and b are drawn along the liver contour with N pixels away from liver

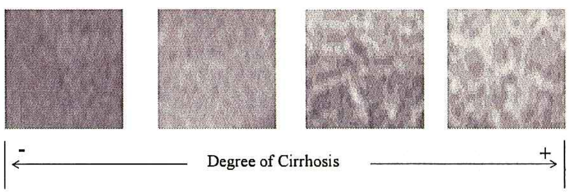

Fig. 3. Different texture patterns of liver tissue from normal (left) to cirrhosis (right).

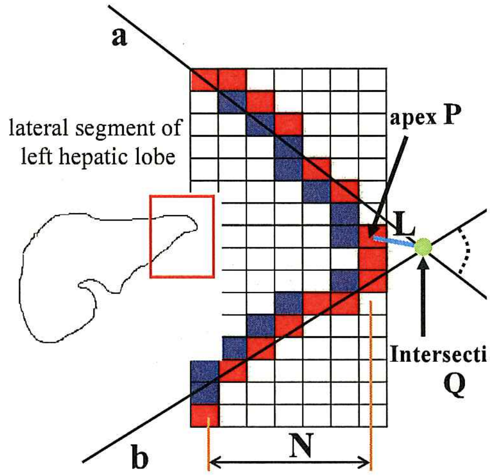

Fig. 2. Method for determining the degree of angle θ and the distance L

vertex P, by using linear least square method. Two shape features angle θ and the distance L from P and intersection Q of two lines are calculated as shown in Fig.2. In this study, N is selected as 20 pixels. Generally, these two features tend to have larger values in cirrhosis cases than in normal cases.

D. Texture analysis of the Liver

The regenerative nodules and fibrosis becomes prominent as cirrhosis progresses, and computerized recognition of the degree of reformed parenchymal texture in cirrhosis has a potential to judge how cirrhosis is advanced. Figure 3 shows some different texture patterns of liver tissue from normal (left) to cirrhosis (right). Texture contains important information, which is used by humans for the interpretation and the analysis of many types of images. Texture refers to the spatial interrelationships and arrangement of the basic elements of an image. The Grey Level Difference Method (GLDM) is very powerful for statistical texture description in medical imaging, especially in Ultrasonic, MR and CT image analysis. Before calculating the texture features, normalization of each image is needed. The resolution of an original MR image is firstly dropped from 16 bits to 4 bits, and then the Sobel operator is employed to obtain the edge image, from which the variation of gray values in different images is limited in a small range.

The texture features are extracted within the 32*32 ROIs selected in the liver region by the method introduced by Haralick et al. [8], which is based on the estimation of the second-order joint conditional probability density functions $f(i,\delta)$ that two pixels with distance d in direction specified by the angle θ, have intensities of gray level difference i, where $\delta=(d,\theta)$. In our experiment, second order probability density function is considered in the 0, 45, 90, 135 degrees direction and the distance parameter d was set to value 1. Based on the

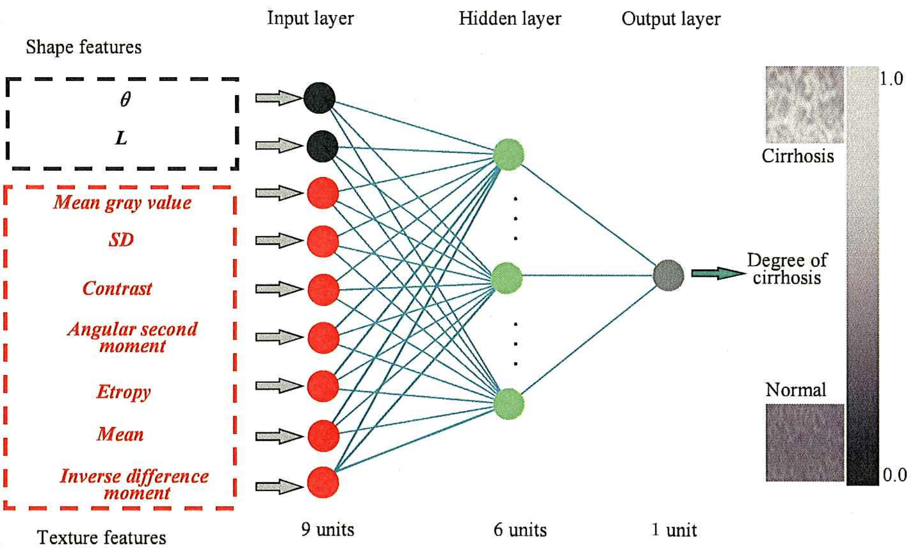

Fig. 4. ANN structure for calculating the degree of cirrhosis

probability density functions the following texture measures are computed: 1) Contrast, 2) Angular second moment, 3) Entropy, 4) Mean, and 5) Inverse difference moment, as follows:

$$Contrast = \sum_{i=0}^{N-1} i^2 f(i \mid \delta) \quad (1)$$

$$Angular \quad 2nd \quad Moment = \sum_{i=0}^{N-1} f(i \mid \delta)^2 \quad (2)$$

$$Entropy = \sum_{i=0}^{N-1} -f(i \mid \delta) \log f(i \mid \delta) \quad (3)$$

$$Mean = \sum_{i=0}^{N-1} i\, f(i \mid \delta) \quad (4)$$

$$Inverse \quad Difference \quad Moment = \sum_{i=0}^{N-1} \frac{f(i \mid \delta)}{i^2 + 1} \quad (5)$$

In addition, for each ROI, the mean gray level and standard deviation were also computed and used as features. To avoid the affect of portal veins and hepatic veins, a ROI will be ignored if there are big vessels inside.

E. MR Imaging of the Liver

Twenty-four patients underwent MR imaging with a 1.5-T superconducting magnet (Signa Horizon; GE Medical Systems, Milwaukee, Wis.). The gadolinium-enhanced gradient-recalled-echo portal venous images were obtained using a phased-array body multi-coil with the following settings: echo time (TE) 1.6 ms, repetition time (TR) 150 ms, flip angle 90°, matrix 512 × 512, 26-second breath-hold acquisition. Images were obtained after an antecubital intravenous bolus injection of 0.1 mmol/kg of gadopentetate dimeglumine(Gd-DTPA) (Magnevist; Schering AG, Berlin, Germany) followed by 15 ml of sterile saline solution flushed. The scan timing was 60 seconds after initiating the contrast injection. The presence of cirrhosis was confirmed by two experienced radiologist (H.K., M.K.) in the 24 patients including 14 patients with cirrhosis and 10 without. From all of the MR images in each case, we selected one gadolinium-enhanced late-phase MR image depicting the largest liver area.

F. Classification by ANN method

Artificial neural network (ANN), which has been successfully applied in many fields on medical imaging [9-12], is easy for less experienced doctors to make a correct diagnosis by generalizing new inspections from past experience. Our previous studies [13, 14] demonstrate that ANN technology is useful for the diagnosis of focal liver disease, and we also select this model to extend to the cirrhosis study. We construct a fully connected neural network as shown in Fig. 4, which is a conventional three-layer feed-forward neural network with 9 input units, 6 hidden units and 1 output units. The network is trained by using the well known backpropagation (BP) algorithm [15]. After establishing the relationship function between the inputs and outputs, we can apply the ANN to the doctors' practical routine inspection to test the generation ability of ANN. The 9 input units are seven features from texture analysis integrated with two features from shape analysis. The output is the degree of cirrhosis. One hundred ROIs selected from 3 normal cases and 3 cirrhosis cases are used to train the ANN, and other 7 normal cases and 11 cirrhosis cases are used to test the performance of ANN. A liver is

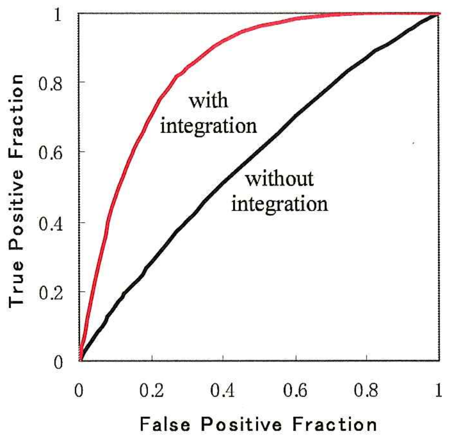

Fig.5 The ROC curves obtained with and without integration of shape features for differentiation of cirrhosis in MR images.

regarded as cirrhosis if the percentage of the ROIs with a degree over 0.5 is greater than 50%. The evaluation performance is undergone with and without the integration of shape features.

III. Results And Discussion

The initial experimental result showed that the ANN based method classified liver cirrhosis with a training accuracy of 100% on the 100 ROIs in the training set. In testing of the whole liver region, 82% (9/11) cirrhosis and 100% (7/7) normal cases were correctly differentiated from 18 test cases by using the sharp and texture analysis, comparing with the result of 55% (6/11) in cirrhosis and 100% (7/7) in normal case by using the texture analysis only. According to the ROC analysis, Az value is improved from 0.57 to 0.84 by integrating the shape features into ANN inputs as shown in Fig.5.

The two lost cirrhosis cases had very similar shape feature values as normal liver, this is due to the fact that the liver may change its shape in different sleeping postures, and the shape features may also be affected by the scanning position only using one 2D slice. Our next step is to calculate 3D shape features to solve this problem, since the dullness of the left lobe is the same no matter how the shape is varied. Furthermore, the CAD system is expected to be able to differentiate micronodular cirrhosis, macronodular cirrhosis and mixed type into different categories by ANN.

IV. Conclusion

The shape features was complementary to the texture analysis of cirrhosis on MR imaging. This experiment demonstrates the ability of ANN to fuse the complex relationships among the imaging findings in MR images, and the ANN-based software may be useful to differentiate cirrhosis in clinical practice.

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