

Texture Analysis of Ultrasonic Liver Image Based on Wavelet Transform and Probabilistic Neural Network

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Abstract

In this paper, a new liver texture classification method based on discrete wavelet transform (DWT) is proposed to differentiate ultrasonic normal liver image from fatty liver. The low frequency coefficients of transformed image denote the approximation of the image, and the high frequency coefficients denote the details of the image. So the character deduced from DWT coefficients can embody texture feature of images. The mean and standard deviation of transformed sub-image are extracted.

Neural networks are employed to classify pattern based on learning from examples. The Probabilistic Neural Network (PNN) develops from radial-basis-function neural network (RBFNN) and approaches the Bayes theorem maximum posterior probability, thus it is employed as a classifier in our method.

Then the above statistical features are applied for texture classification by PNN. Experimental results show that statistical features extracted from DWT coefficients achieve good effects.

1. Introduction

Ultrasonic imaging is a popular and non-invasive tool frequently used in the diagnoses of liver diseases. The ultrasonic liver images have various granular structures described by "texture" [1]. Therefore, the analysis of ultrasonic images can be viewed as the problem of texture classification. The major problem of texture classification is feature 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 [2].

The statistical approach can also be broadly divided into two categories, which based on spatial domain and based on transformed domain. A considerable number of image texture analysis techniques was developed over the years, such as the gray histogram statistics, the gray difference histogram statistics[3], the spatial gray dependence matrices[4], the fractal dimension texture

analysis and the gray run length statistics[5] etc[6], the above techniques are based on space domain. The most common texture analysis methods based on transformed domain are the Fourier power spectrum and the wavelet transformed analysis [7]. Each of the above methods has its own peculiarity in performance [8][9]. In our research work, observing the wavelet transformed liver images, intuitively, the coarser granularity is dominated by larger scale features, while the finer granular structure is dominated by smaller scale features. Therefore, it would be a probable strategy to capture the granular information by utilizing wavelet transforms multi-scale analysis approach to seek one or some scales on which the extracted features are sufficient to discriminate the considered liver diseases [10].

Wavelet transform becomes an active area of research for signal analysis. Wavelet transform is a multi-scale analyzing tool, which can be used to extract multi-scale information from ultrasonic liver images. So, the wavelet transform is applied to texture analysis to differentiate normal liver from fatty liver in this paper [11].

The paper is organized as follows: Firstly, DWT is applied on the normal and fatty liver images and statistical features such as mean and standard deviation are extracted from the approximation and detail sub-band of DWT decomposed images at different scales. Then the various combinations of the above statistical features are applied for texture classification and a set of best feature vectors are chosen. Subsequently, neural networks are employed to classify pattern based on learning from examples. The Probabilistic Neural Network (PNN) is employed as a classifier in our method [12].

2. Texture feature extraction and selection

The wavelet transform can provide a precise and unifying framework for characterizing a signal at multiple resolutions. For wavelet application, the first issue is to select the proper mother wavelet possessing desirable characteristics. The best mother wavelet

should serve to decrease the correlation among the different liver status for the convenience of the successive discrimination task. After more tests, we choose Daubechies4 as the mother wavelet in our study [10].

The image is actually decomposed into four sub-bands and critically sub-sampled by applying DWT. These sub-bands labeled H1, V1 and D1 represent the detail information of images, while the sub-band A1 corresponds to approximation information of image. To obtain the next coarse level of wavelet coefficients, the sub-band A1 alone is further decomposed and critically sampled. Similarly, to obtain further decomposition, A2 will be used. This process continues until some final scale is reached. The result of three-level wavelet decomposition is shown in Fig1.

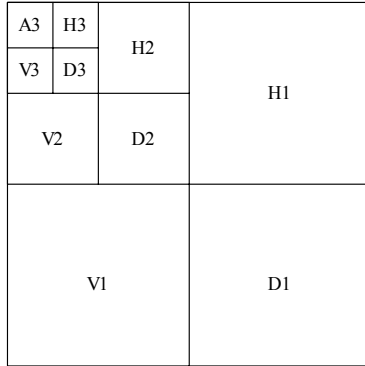


Figure 1. Three-level decomposition of DWT

The values or transformed coefficients in approximation and detail images (sub-band images) are the essential features, which are shown here as useful for texture analysis and discrimination. As micro-textures or macro-textures have non-uniform gray level variations, they are statistically characterized by the features in approximation and detail images. In other words, the values in the sub-band images or their combinations or the derived features from these bands uniquely characterize a texture. The features obtained from these wavelet transformed images are shown to be used for texture analysis and feature extraction [7].

Then, mean and standard deviation of approximation and detail sub-bands of three level decomposed images (i.e. Ak, Hk, Vk and Dk; for k = 1, 2; 3) are calculated as feature parameters by using the formulas given in the Eqs. (1) and (2) respectively.

$$Eg_i(x, y) = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N |g_i(x, y)| \quad \text{Eqs. (1)}$$

$$Dg_i(x, y) = \sqrt{\frac{\sum_{x=1}^M \sum_{y=1}^N [|g_i(x, y)| - Eg_i(x, y)]^2}{MN - 1}} \quad \text{Eqs. (2)}$$

Where $g_i(x, y)$ is the transformed value in $g(x, y)$ for any sub-band of scale i . $M \times N$ is the size of the sub-band. Then 24 statistical feature parameters are calculated. To decrease redundancy of the feature parameters, a forward search procedure is applied to select useful features from the derived statistical feature set. After much work we concludes that the mean and standard deviation of the transformed sub-band images A2, H2, V3, D3, i.e. the approximation coefficients of 2-level DWT decomposed images, the horizontal detail coefficients of 2-level DWT, the vertical detail coefficients of 3-level DWT and the diagonal detail coefficients of 3-level DWT are best representative of the original image [13][14].

The normal and fatty images are shown as figure 2. Firstly image pretreatment should be done by imaging denoising and enhancement. Then the above chosen parameters derived from 10 normal liver images and 10 fatty liver images are shown in table 1 and table 2. From the experiments data we can conclude that the echo of fatty image is stronger than that of the normal, and the normal images contain more high frequency components than the fatty, which are consistent with the visual effect of the lesions.

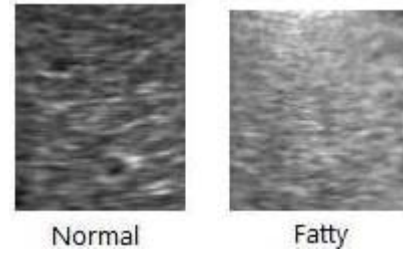


Figure 2. Ultrasonic image

3. Texture classification

As artificial neural network imitates the way which human brain deals with information, it has many advantages such as self-organization, self-learning, adaptive ability, strong fault-tolerant ability, distributed memory and parallel processing function. Artificial neural network has already been widely used in various pattern recognition technologies [15]. 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. PNN develops from radial-basis-function neural network (RBFNN) and approaches the Bayes theorem maximum posterior

Table 1. Feature parameters derived from normal liver image

	ma2	sa2	mh2	sh2	mv3	sv3	md3	sd3
1	9.4563	1.8642	1.6515	2.3438	1.9408	2.7125	1.4271	1.4271
2	9.3430	2.3229	2.5871	3.5560	2.3440	3.1858	2.0867	2.0867
3	8.7498	2.8551	2.9238	3.7408	2.8088	3.9208	2.7003	2.7003
4	8.7080	2.9437	2.8138	3.7308	3.4748	4.5792	2.8652	2.8652
5	9.4444	1.2558	1.4631	1.9136	1.9148	2.6188	1.5919	1.5919
6	8.3931	2.9152	2.7637	3.6462	3.1355	4.0491	3.5501	3.5501
7	9.2770	2.3192	1.9945	2.7236	2.0934	2.6211	1.9582	1.9582
8	6.2256	2.1520	2.0308	2.5733	1.7828	2.3190	1.6221	1.6221
9	7.0292	1.0151	0.8765	1.1982	1.3492	1.7283	1.0569	1.0569
10	6.0010	2.7158	1.9163	2.4268	1.3304	1.8086	2.0585	2.0585

Table 2. Feature parameters derived from fatty liver image

	ma2	sa2	mh2	sh2	mv3	sv3	md3	sd3
1	7.1275	5.2497	2.9254	4.3733	5.5846	7.7178	4.8661	4.8661
2	5.2746	7.2476	4.8149	6.7483	7.2227	9.6639	5.6721	5.6721
3	6.8851	4.0041	3.1680	4.0390	4.7684	6.2978	3.6382	3.6382
4	4.6286	6.3101	4.6012	5.9894	5.9911	8.0761	6.5016	6.5016
5	4.5621	5.9222	3.1887	4.4723	5.2102	7.2137	6.1529	6.1529
6	5.4973	7.9452	4.9543	6.8369	6.2035	7.9068	5.6537	5.6537
7	5.5079	6.6425	3.8765	5.2546	5.3996	6.4560	4.9810	4.9810
8	4.6796	7.5000	4.0730	5.3868	6.3876	8.2352	5.7482	5.7482
9	4.9883	5.9094	4.8086	6.0596	5.6085	7.7744	4.7210	4.7210
10	5.4663	6.0025	4.4573	5.6683	6.5108	9.0407	4.5401	4.5401

probability, thus it is employed as a classifier in our method [15].

PNN is a kind of important deformation of RBFNN. The network structure has three layers: input layer, hidden layer and output layer. Input layer is feature parameters vector. Activation function of hidden layer neurons is Parzen kernel function. Width of Parzen kernel function is adjustable weight in network training which is to make network approaching the best classifier by adjusting weight. The number of hidden layer neuron is the same as the number of input sample vector and output layer selectively makes sum of hidden layer's output. The number of output layer neuron is equal with number of training sample data's types, i.e. output layer is competition layer and every neuron separately corresponds to a data category. PNN model structure is as show in Figure 3.

The i th node's output of hidden layer is $a_i = R(\|X - W_i^1\|b_i^1)$, where X is input sample, $\|\bullet\|$ expresses European distance, $R(\cdot)$ is hidden layer unit's neuron excitation function (kernel function), it has characteristics of local feeling and embodies RBF

network's nonlinear mapping ability; W^1, b^1 is the center and width of hidden layer kernel function, output is linear weighted sums of all nuclear function, the k th node's output is :

$$y_k = \sum_{i=1}^N W_{ik}^2 R(\|x - W^1\|b^1) , \quad (k = 1, 2, \dots, M) ,$$

where W_{ik}^2 is weight coefficient of the i th node in hidden layer to the k th node in output layer. W^1, b^1 is decided by k-mean clustering method [16].

In our research work one hundred sample ultrasonic images are taken out as learning sample to training network. Eight parameters extracted from every sample composes vector feature, i.e. eight-dimensional vector which is as input of PNN to make automatic classification and recognition to the two kinds of images. Another twenty images are taken out as testing sample. Recognition rates of fatty liver and normal liver are above 85% and 82% separately as shown in table 3, where Spd is the adjustable weight. The Recognition Rate is higher than that of the gray difference histogram statistics and the spatial gray level

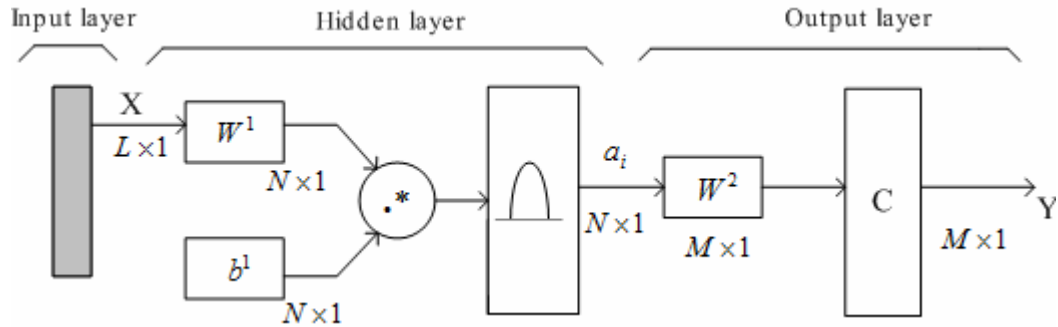


Figure 3. The structure of PNN

dependence matrices techniques. Network simulation output and target vector were processing by linear return analyzed with Matlab, and the correlation coefficient of output vector and target vector is 0.93.

Table 3. Correct classification rates of PNN

Spd	Fatty	Normal
0.01	88%	82%
0.1	87%	85%
0.5	92%	91%
1	85%	87%

PNN absorbs advantages of radial basis function neural network and classic probability density estimation theory. Its mathematical basis of classification is as follows: classification problem is much more linear separable in high dimension space than in low dimension space. Hidden unit makes once transformation which maps input data of low dimension mode to high dimension space in order to facilitate classification and recognition in output layer. Output layer can be regarded as a monolayer perceptron, where weight's learning process is equivalent to looking for a certain hyperplane which can supply best fitting data, thus PNN has more significant advantage in pattern classification than traditional feedforward neural network.

4. Conclusion

Ultrasonic normal liver image and ultrasonic fatty liver image have different granular which is could be described by texture feature such as mean, variance, contrast, correlation etc. Liver images corresponding to different diseases reveal more significant difference in texture after wavelet transformation. So eight texture features were extracted respectively from the two types

images by wavelet multi-resolution analysis. The difference between characteristic parameters is obvious. Then the eight characteristic parameters composed a feature vector which is as the input of PNN to make automatic classification and recognition. Recognition rates of fatty liver and normal liver are above 82%. Therefore, wavelet multi-resolution analysis is a suitable tool to extract texture features from ultrasonic liver images. But as we now know fatty liver still have many types, such as mild, moderate and severe etc., so classification of fatty liver needs some deep research.

5. References

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