A Recognition Method of Medical Image Based on Feature Optimization

Pengpeng Jiao, Yizheng Guo*, Huiming Xia, Xia Lu
Nanjing Normal University Taizhou College,
Taizhou 225300, Jiangsu, China

Abstract—Taking liver CT image as the research object, in order to improve the recognition rate of normal and abnormal images, a recognition method of medical image based on feature optimization is proposed in this paper. The basic idea is that: for the collected CT images, firstly, the color feature, texture feature and shape feature of each image are extracted and used to establish sample database; then the features are normalized between 0 and 1; next, the LLE (Locally Linear Embedding) method is used to reduce the dimension of feature data; finally, the SVM (Support Vector Machine) classifier is used to classify and recognize the test images. The experimental results show that the recognition rate is 86.5%. On the one hand, the recognition rate of multi-features with dimension reduction fusion is higher than that of single feature, at the same time, the LLE dimension reduction method shows strong robustness in manifold learning algorithm.

Keywords - Medical Image Recognition; Feature Extraction; Local Linear Embedding; Support Vector Machine

I. INTRODUCTION

With the development of image technology, images are more and more widely used in medical field. For CT liver images, manual interpretation is influenced by doctors' experience and subjective factors. There may be omissions or misjudgments, and the efficiency of doctors can be reduced with high intensity work. Therefore, the computer is used to find a suitable automatic recognition method to help doctors make auxiliary diagnosis, and it has become an urgent need in the cross field of computer and medicine [1].

By observing the CT images of human abdominal liver, it is found that there are obvious characteristic differences between abnormal images and normal images. The features extracted by computer usually include color feature, texture feature and shape feature [2]. In practical application, it is difficult to describe the content of an image by using only one kind of features [3]. In order to improve the recognition rate of normal and abnormal images, the above three types of features are extracted comprehensively.

There are not only high dimensions but also redundancy among the extracted features. In order to make effective use of various features, after the normalization of features, the LLE method is used to reduce the dimension of feature data in this paper. The nonlinear structure and law can be discovered in high-dimensional sample space and be realized optimization by the LLE method [4]. It can also increase the generalization ability of SVM classifier and reduce its over fitting phenomenon by the combination of dimension reduction using LLE method and the subsequent SVM classifier [5].

The test images are classified and recognized by SVM classifier [6], and the recognition results show that, the feature extracted based on only one kind of feature extraction method can only express part attributes of the image, the classification of single feature cannot take into account many aspects, and the classification based on the multiple features fusion has better performance than that based on single feature.

II. MATERIALS AND METHODS

A. Experimental data

The experimental data was collected from the imaging diagnosis department of a hospital. From more than 40,000 abdominal CT images of nearly 2,000 cases, 2,000 human abdominal images are identified as the experimental data in our study, including 1000 normal medical images and 1000 abnormal medical images.

The gray level of each CT image is 256 which means that pixel value range is 0 to 255. The image resolution is 512*512. There are examples of experimental images in Figure 1. Three abnormal liver CT images are randomly selected on the first line, and three normal liver CT images are randomly selected on the second line.

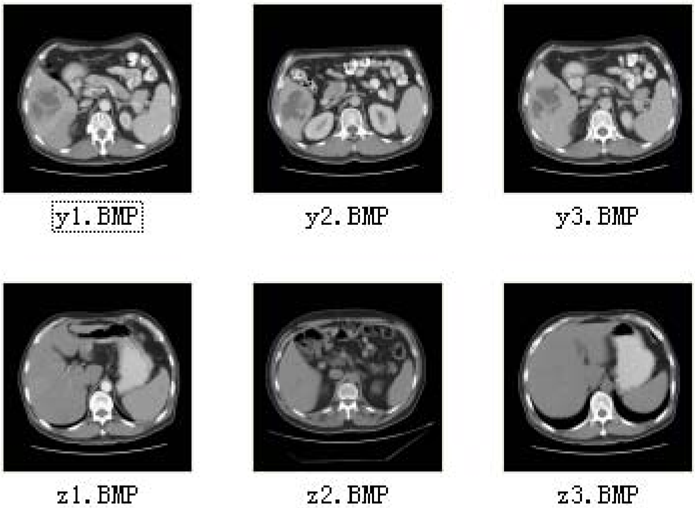

Figure 1. Experimental image example

B. *Experimental methods*

As shown in Figure 2, the research ideas of this paper are given.

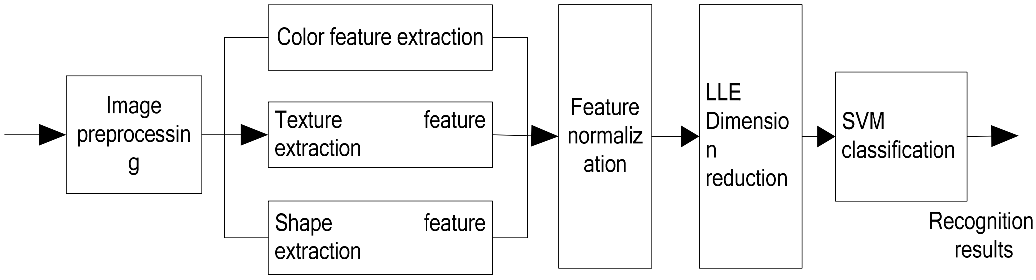

Figure 2. The research ideas of this paper

The main parts are feature extraction, LLE dimension reduction and SVM classification. Their detailed description will be gradually expanded later. Finally, the experimental results and discussion are given.

III. FEATURE EXTRACTION

A. *Gray feature extraction*

Color feature is the most direct visual feature to describe image content. Liver CT image is a typical gray image; therefore, it is necessary to extract the features reflecting the gray distribution of the image. Firstly, the definition of image gray histogram can be expressed by equation (1).

$$H(i) = \frac{n_i}{N} \qquad i = 0,1,\cdots\cdots,L-1 \tag{1}$$

Where L denotes the gray level, i denotes the gray value, n_i denotes the number of pixels of i gray-level, and N denotes the total number of pixels in the image. Here, the following statistics features are extracted based on gray histogram: mean μ 、 variance σ^2 、 skewness μ_s 、 kurtosis μ_k 、 energy μ_N 、 entropy μ_E .

B. *Texture feature extraction*

In this paper, texture features based on Gabor transform are extracted. For a gray image $I(x, y)$ with the given size $P * Q$, its discrete Gabor wavelet transform is as follows:

$$G_{mn}(x, y) = \sum_i \sum_j I(x-i, y-j) g^*_{mn}(i, j) \tag{2}$$

Where, $g^*_{mn}(i, j)$ is the conjugate complex number of the self-similar function $g_{mn}(i, j)$, and i , j is the variable of the filter template size.

The transformed coefficient amplitude series $E(m,n)=\sum_x\sum_y |G_{mn}(x,y)|$ are calculated in different directions and scales, and the amplitude values of these coefficients represent the energy of the image in different directions and scales. The mean value μ_{mn} and standard deviation σ_{mn} of coefficient amplitude sequence are used to construct feature vector f , and it is used to describe image texture.

$$\mu_{mn} = E(m,n)/PQ \tag{3}$$

$$\sigma_{mn} = \sqrt{\sum_x\sum_y (|G_{mn}(x,y)| - \mu_{mn})^2} \,/\, PQ \tag{4}$$

In this paper, $s=4$, $k=5$, the feature vector of each image is $f=(\mu_{00},\sigma_{00},\mu_{01},\sigma_{01},\ldots,\mu_{34},\sigma_{34})$, that is, the Gabor texture features with 40 dimensions are extracted from each image.

C. Shape feature extraction

For an image $f(x,y)$ which size is $M\times N$, its $p+q$ order geometric moments is defined as follows:

$$M_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} i^p j^q f(i,j) \tag{5}$$

Where, $i\in M$, $j\in N$, p and q are constants.

Let $\mu_{pq}=M_{pq}/M_{00}^r$, $r=(p+q+2)/2$, seven moment invariants $M_1,\cdots M_7$ are deduced as the shape features of the image. Accordingly, seven moment invariants can be extracted as shape features of the image.

IV. DIMENSION REDUCTION AND CLASSIFICATION

A. Dimension reduction based on LLE

Through the above methods, three types of features are extracted from each image, with total of 53 dimensions. It includes 6-dimensional gray-scale features based on gray-scale histogram, 40-dimensional texture features based on Gabor wavelet transform, and 7-dimensional shape features based on moment invariants. They compose the feature vectors representing the contents of medical images, but their numerical ranges are different. Therefore, it is necessary to normalize the extracted features by standard deviation transformation and range transformation, and all features are normalized to [0, 1], thus the influence of dimension on classification is eliminated.

Then, the LLE method is used to reduce the dimension of features. In this method, it is assumed that each sample point can be linearly reconstructed by the combination of its nearest neighbor points in the local case, and then the local geometric structure existing in the sample data can be described by the reconstruction coefficient.

Let the input high-dimensional space sample set be $X=\{X_1,X_2,\ldots X_n\}, X_i\in R^D$. After mapping X to a low dimensional space, it becomes $Y=\{Y_1,Y_2,\ldots Y_n\}, Y_i\in R^d$. By K Neighborhood method or ε neighborhood method, the K Data points nearest to the target sample point is found and used as the adjacent points of the target point.

The cost function is as follows:

$$\varepsilon(Y) = \sum_{i=1}^{n}\left\| Y_i - \sum_{j=1}^{K} W_{ij}Y_{ij}\right\|^2 \tag{6}$$

Where, W_{ij} is the reconstruction weighted value between X_i and X_{ij} , X_{ij} represents the j nearest neighbor point of X_i , and satisfies $\sum_j W_{ij}=1$, if X_j is not the nearest neighbor point of X_j, $W_{ij}=0$, and the smaller the cost function is, the better the reconstruction is.

The constraints are as follows:

$$\begin{cases} \min \sum_{i=1}^{n} \left\| Y_i - \sum_{j=1}^{K} W_{ij} Y_{ij} \right\|^2 = \min(YMY^T) \\ The\, constraints: \quad YY^T = I, \sum_i y_i = 0 \end{cases} \tag{7}$$

Where, $M = (I - W)^T (I - W)$ is a sparse matrix, and the Eigenvector corresponding to the smallest（$d+1$） eigenvalues of M is needed to solve. The low dimensional manifold Y is composed of the second to the （$d+1$） eigenvectors.

B. SVM Classification based on SVM

SVM has become the most popular and powerful tool to solve classification and regression problems. The classification functions of SVM are as follows:

$$h(x) = \mathrm{sgn}(\sum_{i=1}^{S} \alpha_i^* \cdot y_i \cdot K(x_i, x_j) + b^*) \tag{8}$$

$$s.t. \quad \sum_{i=1}^{S} \alpha_i \cdot y_i = 0, \quad 0 \le \alpha_i \le C \qquad \forall i \tag{9}$$

Where, α is the Lagrange factor, K is the kernel function, C is the penalty factor.

At present, the most studied kernel functions are polynomial kernel function (Poly), radial basis function (RBF) kernel function and Sigmoid kernel function. Different kernel functions produce different classification results. RBF function is a typical representative of local kernel, which has better local characteristics and interpolation ability, but it is weak in generalization performance; while Sigmoid kernel has good global classification performance and generalization ability, but it is weak in learning ability.

In this paper, these two kinds of kernel functions are combined to form a hybrid kernel function, which still meets the kernel function conditions.

$$\begin{aligned} K(x,y) &= \delta K_{sigmoid}(x,y) + (1-\delta) K_{rbf}(x,y) \\ &= \delta \tanh(\upsilon(x_i \bullet x_j) - r) + (1-\delta)\exp(-\gamma \|x-y\|^2) \end{aligned} \tag{10}$$

Where, $\delta \in (0,1)$, δ is the weight of the kernel function.

V. EXPERIMENTAL RESULTS AND DISCUSSION

In order to verify whether the fused features can better express the content information of the original medical image, the single class features and the fused features are classified and recognized respectively in the experiment. In the image database, 50 normal and abnormal images are selected as training samples, and its purpose is that the input liver images are divided into normal and abnormal types. The experimental results are shown in Table 1.

Table 1. The comparison of different features classification results

features/recognition rate	**200 images**	**500 images**	**800 images**
gray histogram features	38.5%	42.8%	39.5%
Gabor texture features	76.0%	75.8%	77.3%
moment invariants shape features	33.5%	29.2%	32.3%
feature fusion using LLE	85.0%	86.4%	86.5%

The results show that the fused features can better express the content of medical liver CT image, and a higher recognition rate is got.

At the same time, in order to verify the dimension reduction effect of the LLE method, there is a horizontal comparison between the LLE method and the typical Manifold Learning methods such as the ISOMAP (Isometric Mapping) method and the LE (Laplacian Eigenmaps) method. The results are shown in Figure 3.

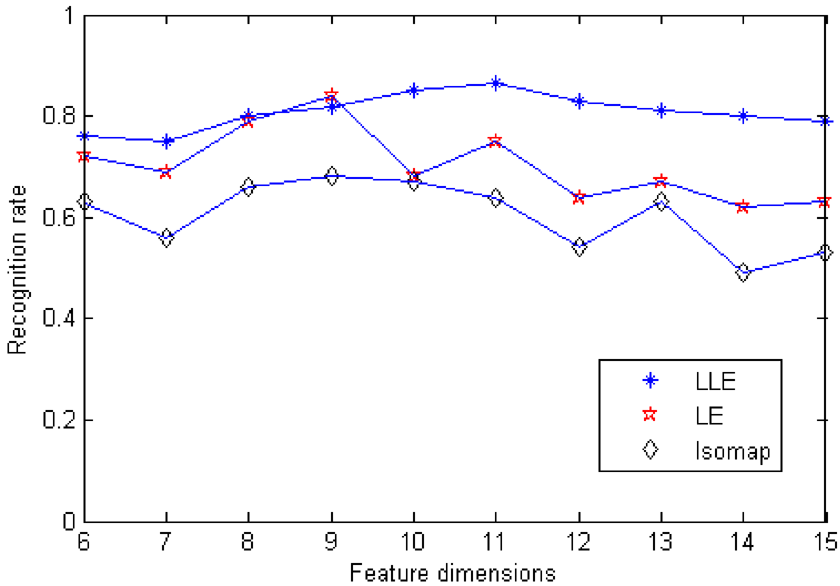

Figure 3. Comparison of recognition rate among LLE and other dimension reduction methods

The experimental results show that the LLE method has better robustness than other typical Manifold Learning methods.

In order to achieve higher recognition rate, on the one hand, the image before feature extraction can be segmented before feature extraction in image preprocessing, on the other hand, other suitable feature extraction method can be further found.

VI. Conclusion

In this paper, a recognition method with feature optimization is proposed for medical liver CT image, and is used to identify whether the image is abnormal. After gray features, texture features and shape features are combined and fused by the LLE method, a higher recognition rate can be got, which verifies the feasibility and effectiveness of this method. The recognition results can provide reference for doctors to assist diagnosis. Considering the complexity of the original medical liver CT image content information, it is worthy of further study that how to realize automatic and accurate multi-category recognition.

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