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Selection of Optimal Shape Features for Staging Hepatic Fibrosis on CT Image

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Computer-aided diagnosis of hepatic fibrosis is playing an increasing role in clinical visits, while the study based on shape features diagnosis is still in the exploratory stage. In order to improve efficiency of interpretation of medical images and diagnostic accuracy, a novel method for informatics feature selection from hepatic shape is proposed in this paper. First, the contour profile of liver is extracted from contrast-enhanced CT images. Then a difference edge curve is obtained from substation of the profile with the polynomial fitting curve, from which ten surface shape features are calculated for the input parameters of the SVM classifier. Finally, feature selection algorithm with cross-validation leave-one-out method is applied to check each combination of all features to provide the accurate rate of staging the fibrosis degree. The result shows that the optimal number of features ranges from two to six among all ten features; statistical analysis shows that maximum roughness depth (R_{max}), maximum profile valley depth (R_p), maximum profile peak height (R_m), mean spacing of the profile irregularities (S_m) and mean spacing of local peaks of the profile (S) have the greater weight than the other features. The experimental result indicates that the accuracy rate of shape feature is considerably higher than other types of features.

Keywords: Computer-Aided Diagnosis, Hepatic Fibrosis, Waviness of Surface, SVM Classification, Feature Selection.

1. INTRODUCTION

With the development of medical imaging and computer-aided technology, medical imaging technology has become one of the fastest growing fields in medicine. In liver studies, various features can be extracted from CT or MRI images to help radiologists diagnose and analyze liver lesions quantitatively. Among them, imaging features based on texture and shape have attracted more and more attention by experts and scholars. Gao et al.[1] proposed a texture image recognition method based on the correlation coefficient. The recognition rate of the diaphragmatic peritoneal ultrastructure under electron microscope texture image reached an accuracy of 92%. The multiple sclerosis (MS) research team[2] applies texture analysis technology to the field of microscopic characteristics of MS in cerebral white matter, realizing the classification prediction between the normal cerebral white matter and pathological groups. Guo et al.[3] developed a recognition method between normal livers and abnormal livers based on Gabor wavelet texture features to reach a higher recognition rate of 81.5%. Krusinska et al.[4] used shape features as a distinction analysis method to predict the histopathology of liver biopsy specimens. Bai et al.[5] used the peripheral morphological characteristics that divide edge of liver tumors into three categories, indicating that CT perfusion imaging tumor edge can reveal histopathological features and indirectly reflect the change of liver cancer angiogenesis. Computer aided diagnosis can effectively help doctors analyze the patient condition, and seeking effective diagnosis parameters may improve the performance of CAD algorithms. Elimination of redundant or irrelevant features, as well as optimization of the number of features, is a big challenge in medical image processing.

At present, there is no unified shape model and feature selection method due to the diversity of different morphological features and their combination probability. In order to find an effective and accurate method to diagnose liver fibrosis, we propose a quantitative approach for selecting effective shape features

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from the roughness parameters of micro surface that is widely used in mechanical engineering.[6]

2. MATERIALS AND METHODS

In this experiment, ten shape parameters calculated from segmented liver surface are inputted into SVM for the classification of hepatic fibrosis into two groups, from which accurate rate (AR) is derived by comparing to the gold standard with leave-one-case-out validation method. Then optimal feature numbers, optimization of feature combination and ranks of feature contribution are calculated by statistical analysis of AR results.[7]

2.1. Medical Image Materials

All of the datasets used in the experiments is provided by the radiology department of First Affiliated Hospital in Guangxi Medical University. Abdominal CT images are acquired from January 2010 to February 2011. A total of 48 cases with different liver-related diseases are collected, including cases confirmed by liver biopsy, patients with chronic hepatitis B, typical cirrhosis patients, and patients without liver biopsy and no history of liver-related diseases. Based on standard of liver fibrosis classification, the data set is divided into normal group S0, mild liver fibrosis S1 & S2, severe liver fibrosis group S3 & S4 and cirrhosis group CIR.

2.2. Liver Contour Extraction

This experiment focus on subtle changes of shape features. We use liver profile drawn manually by radiologists as the gold standard of this study. For the selection process of liver profiles, as the left liver lobe is more likely to be deformed and the formation of nodes is easier to be observed and identified compared with right lobe, we choose the partial profile in three liver areas, namely inner lower segment of left lobe of liver, inferior segment of left lateral liver and superior segment of left lateral liver, as shown in Figure 1.

2.3. Calculation of Shape Features

Shape features are intuitive and can be observed and detected easily, and thus it plays a profound role in image analysis and application. Ten most representative features[8–10] are chosen as the profile features of liver based on the roughness of micro-mechanical surface in mechanical engineering, which are

(1) roughness average (R_a);
(2) root mean square roughness (R_q);
(3) maximum roughness depth ($R_{\max}$);
(4) maximum profile peak height (R_m);
(5) maximum profile valley depth (R_p);
(6) mean spacing of the profile irregularities (S_m);
(7) mean spacing of local peaks of the profile (S);
(8) ten-point average roughness (R_z);
(9) peak density of the outline (D);
(10) profile bearing length ratio (T_p).

The measurements of the shape features are described by the following formula and demonstrated in Figures 2–4.

Roughness average R_a is a basic parameter of average profile surface roughness that is the first-order linear measurement of the degree deviating from the centerline.

$$R_a = \frac{1}{l}\int_0^l |y|\,dx = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{1}$$

Where l stands for the sampling length of profile that is a unit measuring features; y is a mathematical function of profile; n is a set of points in uniform distribution.

The root mean square roughness R_q is the second-order linear measurement of the degree deviating from the centerline. It is based on arithmetical mean deviation, and it is a standard for the degree of profile deviating from the centerline.

$$R_q = \sqrt{\frac{1}{l}\int_0^l y^2(x)\,dx} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2} \tag{2}$$

The values of R_a and R_q represent the average roughness of profile. Profile shows an apparent surface roughness as the values increase, and conversely, profile shows smoothness.

The maximum roughness depth $R_{\max}$ is the vertical distance between peak and valley, which describes the most prominent part of the profile surface.

$$R_{\max} = y_{p\cdot\max} + y_{v\cdot\min} \tag{3}$$

Correspondingly, maximum profile peak height R_m and maximum profile valley depth R_p is the maximum measure for deformation on the centerline in the positive direction and negative direction, respectively. R_m and R_p represent the maximum deformation in these two directions.

$$R_m = \max(y_i) \quad i = 1, 2 \ldots v \tag{4}$$

$$R_p = \max(y_i) \quad i = 1, 2 \ldots p \tag{5}$$

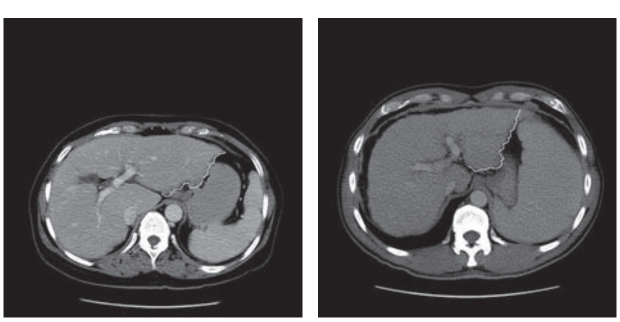

Fig. 1. Liver contour curves used in the experiment.

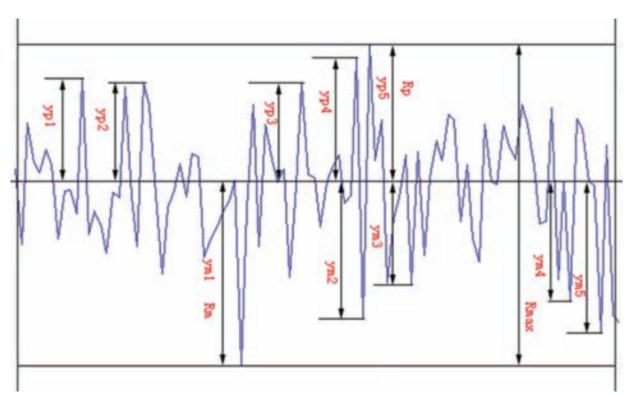

Fig. 2. Feature definition of $R_{\max}$, R_m, R_p, and R_z.

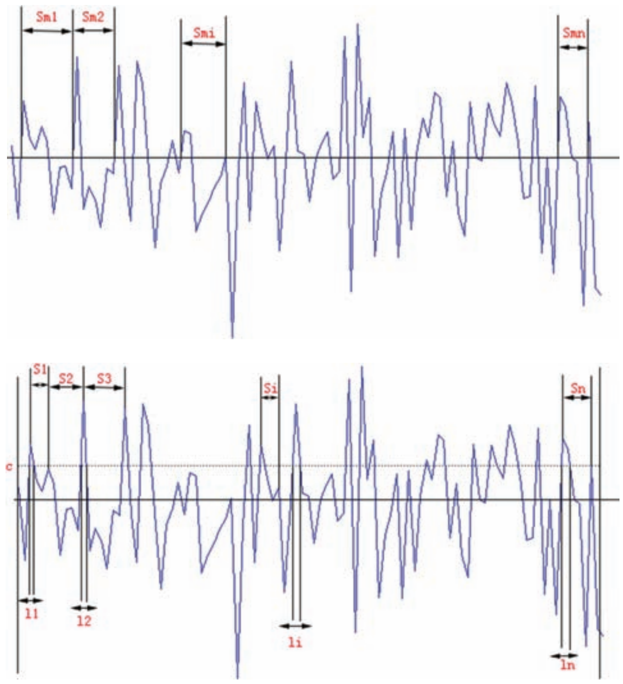

Fig. 3. Feature definition of S_m, S and T_p.

Average point height of irregularities R_z, otherwise called ten-point average height, is a comprehensive description of higher peak and lower valley on the profile.

$$R_z = \frac{1}{5}\left(\sum_{i=1}^{5} y_{p_i} + \sum_{i=1}^{5} y_{v_i}\right) \tag{6}$$

Where y_{p_i} stands for the maximum peak of the first i, and y_{v_i} stands for the minimum valley of the first i. $R_{\max}$, R_m, R_p and R_z describe profile in the vertical direction, and they are measurements of roughness in the vertical height direction.

Mean spacing of the profile irregularities S_m is an average of distances of the micro-roughness in sampling length. It was obtained by measuring the zero crossing density on the profile. The spacing of the unimodal profile represents a length projected by the distance between the peaks of two-neighbor single peak. The mean spacing of local peaks of the profile S is the arithmetic mean value of the spacing of the unimodal profile. The peak density of the profile D is a measurement of S_m in a unit length of a profile.

$$S_m = \frac{l}{n_0} = \frac{l}{\text{num}(x(y=0))-1} \tag{7}$$

$$S = \frac{1}{((p+v)/2)+1} \sum_{i=1}^{\max(p,v)} |p_i - v_i| \tag{8}$$

$$D = \frac{l}{S_m} \tag{9}$$

Where, p is the peak of profile; v is the valley of profile, n_0 is the number of zero crossing point. S_m, S and D describe profile in the transverse direction, and they are measurements of roughness in the spacing.

The profile bearing length ratio T_p is the ratio of bearing length to sampling length. Letting the cutting depth be 15% from the peak to line c, which is parallel to the mean line of profile. The fraction of the line which lies within the profile $l1, l2, \ldots, ln$ are called bearing length, which can be expressed by:

$$\begin{gathered} l_i = x_{i+1} - x_i \\ y_i, y_{i+1} = R_p \cdot c \end{gathered} \tag{10}$$

T_p describes the profile in both the vertical and transverse direction, reflecting the microcosmic shape characteristic.

$$T_p = \frac{\eta_p}{l} = \frac{l_1 + l_2 + \cdots l_n}{l} \tag{11}$$

2.4. Experimental Flowchart of Feature Selection

For each edge curve, ten roughness features are extracted on the basis of above formulations as the input of the SVM classifier.[7] We have chosen the radial basic core function (RBF), which is widely known and used in classifications, as the kernel function of the SVM classifier in this experiment. Feature selection includes two sections: optimizing number of input vectors and optimizing weight of each shape features. Leave-one-out cross-validation method is used to evaluate each input datasets providing classification results with accuracy rate (AR). Maximum average accuracy and the choice of corresponding features can be obtained on the basis of the AR value. The experiment flow chart is shown in Figure 4.

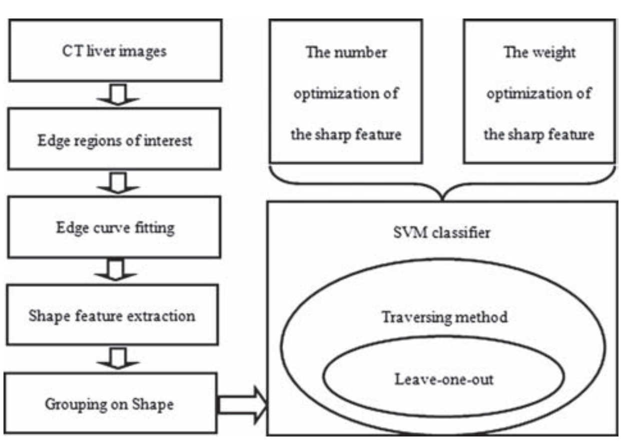

Fig. 4. Flow chart of feature selection.

3. STATISTICAL ANALYSIS OF INPUT NUMBER OF FEATURES

Based on the current stage of computer-aided diagnosis on medical images, selection of characteristic parameters is still in the exploratory stage, and there is no standard method of selecting features for reference. In order to make the statistics of maximum average accuracy corresponding to different numbers of shape feature, each number of feature sets in the classification results are grouped in $P_n(k)(k = 1, 2 \ldots 10)$, wherein n represents different input groups, k is the amount of the number of

Table I. Accuracy rate and its corresponding number of features.

Feature number	1	2	3	4	5	6	7	8	9	10
AR	0.87	0.91	0.94	0.93	0.91	0.92	0.88	0.82	0.79	0.78

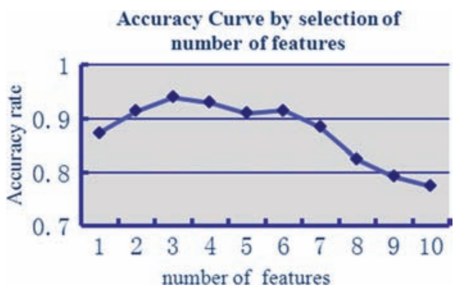

Fig. 5. Accuracy curve by the selection of number of features.

selected features. For example, $P_1(1)$ represents the highest average accuracy rate when selecting one feature as the input on a first class input grouping. It is the criteria of judging the accuracy rate of 10 types of shape in corresponding input groups. The higher the value P, the better the classification result with the currently selected feature quantity. Finally the mean value of $P_n(k)$ in each group is averaged to be the basis of shape feature quantity optimization:

$$\tilde{P}(k) = \frac{1}{7}\sum P_n(k) \quad (k = 1, 2\ldots, 10, n = 1, 2, \ldots, 7) \tag{12}$$

According to the results obtained with different $\tilde{P}(k)$ values in Table I, the AR rate has different performance with the number of the shape features using as an input set as shown in Figure 5.

According to Figure 5, SVM classifier obtains better classification when selecting 2–6 shape features as inputs. If the number of features is greater than 6, the classification results become worse with an increase in the input features; on the contrary, if the number of selected shape feature is too small, the insufficient information will make the classifier hard to classify the samples with less effective inputs. Therefore too many or too few features cannot effectively diagnose liver fibrosis.

4. FEATURE IMPORTANCE ANALYSIS

The weight of a feature refers to the degree of influence that a feature affects the accuracy of classification results. The greater the weight, the greater the feature influences the results of the classification experiment; on the contrary, a smaller weight means a smaller impact of this feature on the classification. According to the probability and statistics theory: A collection of events has occurred for S, $S = \{A_1, A_2, A_3 \ldots A_{n-1}, A_n\}$, the number of A_1 occurred in m replications is *mA1*, if the number of test times m is very large, the frequency *mA1/m* stable swing near a certain value p, and with the increase of the number of tests m, its magnitude swing becomes smaller. p is called the probability of random events A_1:

$$P(A_1) = \frac{mA_1}{m} \tag{13}$$

In order to effectively evaluate the weight of various features, we rearrange all classification results according to the classification accuracy for each combination. From all 2^{10} combination

Table II. **Feature weights in the classification of hepatic fibrosis.**

Shape feature	R_a	Rq	R_{max}	R_m	R_p	S_m	S	R_z	D	T_p
Feature weight	0.15	0.59	0.62	0.64	0.84	0.65	0.78	0.38	0.27	0.37
Normalized weight	0	0.64	0.69	0.71	1	0.73	0.91	0.34	0.18	0.32

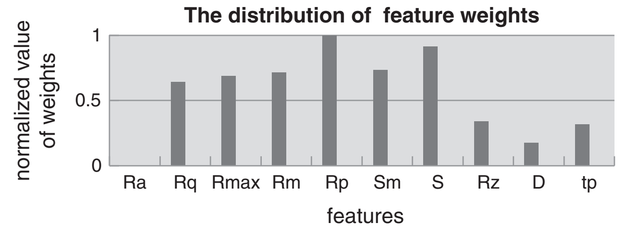

Fig. 6. The distribution of normalized value of weights for ten shape features.

datasets, the frequency of 10 features appeared in all classification combination is statistically counted as the weight of feature that can be expressed by:

$$P(k) = \frac{1}{N}\sum_{1}^{N} n \quad (k = 1, 2, \ldots, 10, n = 0, 1) \tag{14}$$

Where k represents a number of feature, N is the number of classification test, and in our experiment $N = 1023$. n represents the appearance of k feature in each of the combinations validation: if k appears then $n = 1$, otherwise $n = 0$. After calculating the appearing probability of each feature separately, we can obtain the weight value of each feature. In order to visualize the relationships among the weights of individual features as well as the entire weight relationships in the experiment, min–max standardization[11] is applied to mapping the sample weights to a range between [0–1] using linear transformations as follows:

$$W(k) = \frac{P(k) - P(k)_{\min}}{P(k)_{\max} - P(k)_{\min}} \tag{15}$$

Transform function normalizes the feature weights between [0, 1]. If $W(k)$ is closer to 0, that indicates a feature has a small weight and less important to the classification result, whereas $W(k)$ closer to 1 indicates a more significant feature corresponding to a higher weight. The experimental result is illustrated in Table II, and the distribution of normalized value of weights is shown in the Figure 6.

Experimental results show that the number of 3, 4, 5, 6, 7 features, namely $R_{\max}$, R_p, R_m, S_m, S, have larger weights than the other five features, meaning their larger contribution to the classification in this experiment. In other words, they play a more important role in the diagnosis of liver fibrosis with the capability of reflecting the severity of fibrosis more accurately. In mechanical engineering, the representative significance and generally accepted parameters in the measurement of microscopic surface irregularities are R_a, $R_{\max}$, R_p, R_m and T_p, that is highly identical with our results. It is also verified that the results of our classification in feature selection has a theoretical basis.

Comparing with other methods for staging the liver cirrhosis or fibrosis.[12–14] The overall performance calculated by the average sum of maximum AR value of all types number of features is 85.74% by shape features, while 66.83% by texture and 75% by volume. The result implies the efficiency of shape features to the diagnosis of liver fibrosis.

5. CONCLUSION

This study investigates the role of shape features in the classification of hepatic fibrosis by selecting the optimal parameters for building a better Computer-aided Diagnosis system. Ten surface shape features are extracted from a standardized profile of liver. Each combination of these features is selected as input subsets to be checked by using a support vector machine (SVM) with the leave-one-case-out method to differentiate fibrosis into normal or abnormal. The result shows that the optimal number of features is ranged from 2 to 6 among all 10 features; statistic analysis shows that maximum roughness depth ($R_{\max}$), maximum profile valley depth (R_p), maximum profile peak height (R_m), mean spacing of the profile irregularities (S_m) and mean spacing of local peaks of the profile (S) have the greater weight than the other features. The experiment result indicates that the accuracy rate of using shape features for analysis is considerably higher than using other types of features.

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