Multi-Phase CT Image Based Hepatic Lesion Diagnosis by SVM

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Abstract—**In this paper, a novel liver lesion diagnosis approach based on multi-phase enhanced CT images is proposed. Regions of Interest (ROIs) which are drawn by an experienced radiologist are categorized into 4 classes: normal, cyst, haemangioma and hepatic cellular carcinoma. The diagnosis scheme includes 3 steps: feature extraction, feature selection and classification. For each ROI, 3 distinct kinds of features are extracted using First Order Statistics (FOS), Second Order Statistics (SGLCM), and Temporal Features, where 5 different feature sets are constructed respectively to be fed into a SVM-based classifier. Both classification accuracy statistics and Receiver Operating Characteristic (ROC) curve are employed to evaluate performance of different feature sets. Finally, a mixed feature set consisting of reduced FOS, SGLCM and temporal features gives the best classification accuracy of 0.955, 0.972 and 0.964 for normal-abnormal, cyst-otherdisease and carcinoma-haemangioma sub problems respectively.**

Keywords: multi-phase CT image; texture analysis; computer-aided diagnosis; support vector machine

I. INTRODUCTION

Liver diseases nowadays are widely accepted as one of the most life threatening diseases which always occur without pre-warning[1]. The traditional methods to differentiate normal liver tissues from abnormal ones are largely dependent on the radiologists' experience. Thus Computer-Aided Diagnosis (CAD) system based on the image processing and artificial intelligence techniques gain a lot of attentions, since they could provide constructive diagnosis suggestions to clinicians for decision making. The use of image analysis and image quantity techniques has already been proposed in the discrimination of hepatic tissues. Deepalakshmi[2] et al. proposed the use of grey level co-occurrence matrix(GLCM), grey level run length matrix(GLRLM), Law's spectral texture measures, and Gabor wavelet derived texture features in order to discriminate normal, cyst, benign and metastases hepatic tissues through ultrasound images. Chen et al[3] also used GLCM on CT images to derive texture features aiming to training a Probabilistic Neural Network (PNN) for differentiating hepatoma and hemangioma, In [4], Chien-Cheng Lee et al. use Gabor wavelet based texture features and a Support Vector Machine(SVM) for discriminating normal, cyst, cavernous hemangiomas and hepatomas. Gletsos et al. [5] proposed a system in which GLDM based features are fed to a three sequentially placed Neural Networks Classifier to categorize each tissue instance into four classes. In [6], five distinct types(First Order Statistics, SGLDM, GLDM, Law's texture energy measures, fractal dimension texture measurement) of texture features were used by Ioannis K. Valavanis et al. in the task of discriminating hepatic tissue into four classes. Although a lot of endeavor have been devoted into the discrimination of liver tissue characteristics, the result of current systems is still not satisfactory enough which explain the reason why liver CAD system is not as popular as other CAD systems like breast nodule detection or lung nodule diagnosis systems. From the other perspective, it also shows great potential in liver CAD research work.

It is natural to notice that previous works were just using non-enhanced CT images as diagnosing medium. But recently, radiologists find that multi-phase enhanced CT images are of great help in the description of liver lesion pathological characteristics. And temporal dynamic contrast-enhanced images have already been used as an important imaging medium of breast nodule diagnosis systems using MRI (DCE-MRI) [7]. And nowadays iopamidol injection commonly used as a standard contrast agent is widely accepted having no harmful side-effect to human body which makes enhanced CT examination almost a standard routine for every patient who is suspicious of liver problems. In this study, we introduce a novel liver lesion diagnosis approach which is based on the variations of temporal features expressed in multi-phase abdominal CT images. The methods of extracting texture features from different phase images based on their pathology characteristics are explored. Then support vector machine (SVM) method is proposed to do the job of classifying Region of Interest (ROI) of hepatic tissue into four classes: normal liver tissues, cyst tissues, haemangioma tissues and hepatic cellular carcinoma tissues.

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II. METHODS AND MATERIALS

A. Image Acquisition

A total of 131 multi-phase abdominal examinations were collected from Shanghai Renji Hospital. All the cases were pathological diagnosed by the histopathologists using a series of clinical analysis tests including tissue biopsies if needed. All these cases are labeled into four classes, 64 of which are healthy tissues, 14 of which are diagnosed as cyst, 26 of which are accepted containing hepatic cellular carcinoma illness, rest of which are haemangioma instances.

B. Data Preprocessing and Feature Vector Extraction

Boundary of each lesion was drawn by experienced radiologists to avoid the interference of healthy and necrotic tissues. Within the identified lesion, a 16x16 pixels square mostly presenting its pathological activity was extracted as region of interest (ROI). A huge difference between Liver CAD and other CAD like breast CAD [8] and lung CAD [9] is that shape prior has no effect in the detection and diagnosis of hepatic lesions due to the fact that liver disease is prone to diffusing–like and even the same type of the disease always varying greatly in shape from case to case. Therefore texture-based features become the optimal candidate target for feature extraction task. Image texture feature extraction is fully discussed in [10], among these feature the most suitable ones for the liver lesion CT images are selected. Besides, some temporal features which are useful to express temporal change tendency between the different phase enhanced images are also extracted.

1) First Order Statistical Features:

Moment-based image texture features are histogram-based texture features which gives the information of the distribution of image gray-level. Here P(I) is the first order histogram of the image.

a) Moments:

$$m_i = E[I^i] = \sum_{I=0}^{Ng-1} I^i P(I), i = 1, 2... \quad (1)$$

Here m0=1, m1=E [I] is the mean value of I.

b) Central moments:

$$\mu_i = E[(I - E[I])^i] = \sum_{I=0}^{Ng-1} (I - m_1)^i P(I) \quad (2)$$

$\mu_2 = \sigma^2$ is the variance, and μ_3 is known as the skewness and μ_4 as the kurtosis of the image histogram. The variance is a measure of the histogram width, that is, a measure of how much the gray levels differ from the mean. Skewness explains the degree of histogram asymmetry around the mean, and kurtosis describes the sharpness of the histogram [10].

c) Absolute moments:

$$\overline{\mu}_i = E[|I - E[I]^i|] = \sum_{I=0}^{Ng-1} |I - E[I]|^i P(I) \quad (3)$$

d) Entropy:

$$H = -E[\ln P(I)] = -\sum_{I=0}^{Ng-1} P(I) \ln P(I) \quad (4)$$

Entropy expresses the uniformity of histogram.

2) Second Order Statistical Features:

Co-occurrence matrix based image texture features give the information of the relative position of different gray-level pixels in the ROI. The co-occurrence matrix is calculated for d = 1 pixels and the (0,1),(-1,1),(1,0),(-1-,1) four directions are used.

a) Angular second moment:

$$ASM = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (P(i,j))^2 \quad (5)$$

b) Contrast:

$$CON = \sum_{n=0}^{Ng-1} n^2 \{ \sum_{i=0 \wedge |i-j|=n}^{Ng-1} \sum_{j=0}^{Ng-1} P(i,j) \} \quad (6)$$

c) Inverse difference moment

$$IDF = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \frac{P(i,j)}{1 + (i=j)^2} \quad (7)$$

d) Entropy:

$$Hxy = -\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P(i,j) \ln(P(i,j)) \quad (8)$$

3) Temporal Signal Tendency Features:

Fig.1 present a figure describing phase versus intensity curves of typical four different tissue types (normal, cyst, hepatic cellular carcinoma and haemangioma). The temporal patterns of contrast relies on the vascular structures, differences in vessel growth between different hepatic diseases' lesions can potentially be characterized the contrast uptake and washout of the tissue. Vascular tumors of the liver such as hepatic cellular carcinoma, which receive most of their functional blood supply from the hepatic arterial flow will enhance the tumors during the arterial phase on CT images. Normal hepatic parenchyma receive most of their nutrient blood from portal veins and, therefore, will be enhanced during the venous phase. Hepatic haemangioma commonly show progressive enhancement, from periphery to central, from arterial phase to venous and delayed phase images [11]. Cyst is mainly composed of effused fluid, which means that its mean intensity will not have great change during the whole time series. Here S(i) represent the mean pixel value of ROI in different phases, where 0 to 3 stand for pre-contrasted phase, arterial phase, portal venous phase and delayed phase respectively.

a) Relative Signal Intensity:

$$RSI(i) = \frac{S(i)}{S(0)}, i = 1,2,3 \quad (9)$$

This feature is a vector feature which mostly straightforwardly represents the pattern of temporal enhancement.

b) Intensity Change Tendency

$$ICT(i) = \frac{S(i+1) - S(i)}{T(i+1) - T(i)}, i = 0,1,2,3 \quad (10)$$

This feature is vector feature, which represented the time-based derivate of the enhancement.

c) Intensity Change Tendency

$$SER = \frac{S(1) - S(0)}{S(3) - S(0)} \quad (11)$$

According to [12], SER is a great feature which could describe the contrast enhancement pattern of the lesion. Based on the SER, the lesion ROI could be classified into washout, plateau, or persistent enhancement. Washout behavior of lesions has been validated to be highly correlated with tumor angiogenesis. That is, high micro vascular density would probably cause the washout behavior which is typically the case of hepatic cellular carcinoma in our study.

C. *Classifier Selection and Design*

Currently Support Vector Machine (SVM) is widely considered as a great achievement in the research area of machine learning and pattern recognition [11]. SVM is a relatively new and famous machine learning method in constructing a classification function from a set of labeled training sets.

In non-linearly separable cases such as our study, according to Cover's theorem [13], a kernel function is used to project the data from input space into feature space. Commonly the feature space has more dimensions than the original input space. SVM acquire the decision function though minimizing the following optimization problem:

$$\min_{\alpha}[\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j x_i \bullet x_j - \sum_{i=1}^{n} \alpha_j] \quad (12)$$

$$s.t. \sum_{i=1}^{n} y_i \alpha_i = 0, 0 \le \alpha_i \le C, i = 1,2...,n$$

Considering the specific of our study, the RBF kernel is selected:

$$K(x_i, x_j) = (\gamma(x_i \bullet x_j) + a)^d \quad (13)$$

Where x_i and x_j are input vectors made up of one of previously mentioned feature vectors. y_i and y_j are class labels in classification problem and C is a regularization value. Here * represent the inner product operation. γ, a and d are the kernel parameters.

Classification of lesions has been decomposed into a hierarchically 3 steps classification where each step is composed of a supervised two-class classification problem. Through the training set, 3 SVM models are constructed. First SVM model will classify the ROI into healthy and pathological region. If the ROI is classified as pathological region in the first step, then the ROI is again used to be fed into the second model which will label it into cyst and non-cyst. If the diagnosis result is positive (non-cyst) again, the last model will be used to finally classify the ROI into haemangioma or hepatic cellular carcinoma. To obtain the satisfied classification result, a lot of works need to be done. First, each component of input feature vector is scaled into the range [-1, +1]. Then a grid search on C and γ using cross-validation and the one with the best classification accuracy is picked. The SVM-based classification algorithm is fully implemented using the libsvm library [14].

III. RESULTS AND DISCUSSION

Receiver Operating Characteristics (ROC) analysis widely used for evaluation of classifiers and visualization of their performance, especially in the medical decision area [15]. To compare the performance of different classifiers, There are a lot of methods to transfer the two dimensional curve into a scalar value. Among these methods, Area Under Curve (AUC) is one of the most commonly and of effect method [15]. In this study, we use k-fold cross validation method [16] to evaluation the model and corresponding ROC graph Fig. 2 is acquired to analysis the feature set's performance.

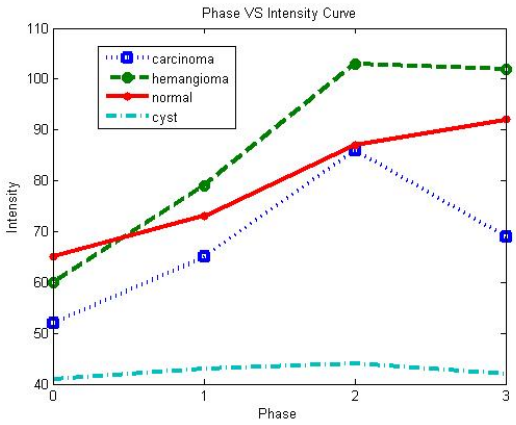

Figure 1. Phase versus Intensity Curves

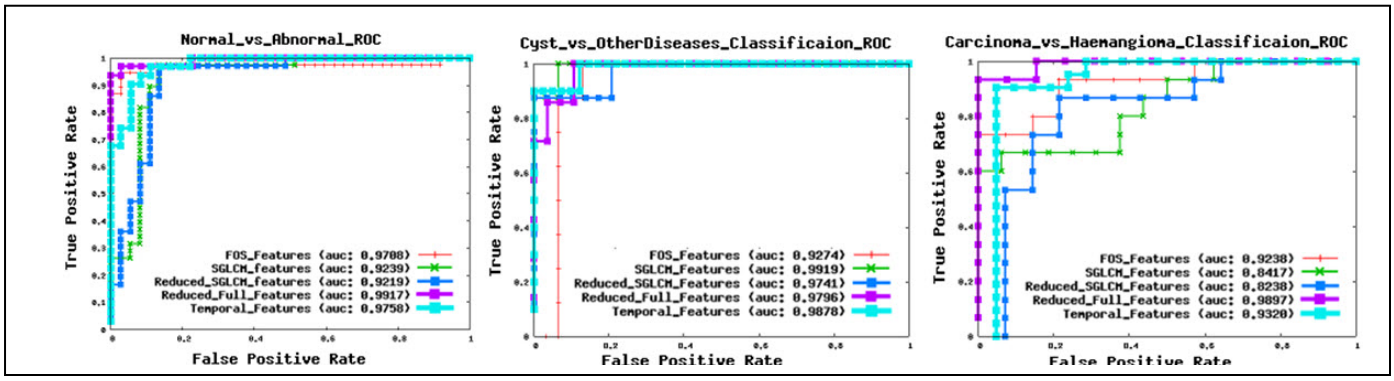

Figure 2. ROC Curves for the classification result

In order to determine the optimal feature set for the discrimination of the lesions, five distinct feature sets are constructed: 7-dimensional FOS features; 32-dimensional GLCM derived features; 9-dimensional temporal features; reduced 8-dimensional GLCM features and reduced 12-dimensional full features respectively. The feature sets of reduced version are the result of a GA-based feature selection module using 32 GLCM features and 24 (7 FOS features, 8 reduced GLCM features, 9 temporal features) features. All the feature sets are applied in every phase of CT images (except for the feature set based on the temporal features which is directly derived from the multiphase images) to obtain the best classification accuracy.

The performance of all classification result is statistically listed in table1-5, categorized by different kind of feature set. From numbers in table2, FOS feature outperform the other texture-based feature set in the classification of normal-abnormal cases, for FOS feature could describe the normal liver tissue well. Similar conclusion is also drawn by [6]. And the facts shown in Table1-5 reveal that the highest classification accuracy of normal-abnormal cases is either in the pre-contrasted phase or portal venous phase of enhanced CT images. This phenomenon is probably caused by the fact that normal liver tissue features could be well extracted from pre-contrasted images and lesion tissue features are mostly enhanced in portal venous phase. Among all the binary classification sub problems, cyst-noncyst case is the easiest to be classified: all the discrimination accuracy is above 90%. This is closely related to its pathological characteristics, whose mean intensity keeps almost constant during the whole enhancement process.

For each feature set, the result of the classifier using the phase leading to the highest classification accuracy is used to draw the ROC graph and corresponding AUC is calculated which lead to Fig.2. According to Fig.2, reduced full feature set outperforms the rest of feature sets in the discrimination of normal-abnormal and haemangioma-carcinoma cases, despite in the statistical analysis, FOS feature set performs better. This pretty makes sense because it used all the FOS, SGLCM and temporal characteristics. In the cyst-noncyst classification, although it is hard to evaluate the effect of different feature sets using statistical analysis, for all the cv accuracy is around 97%, AUC of ROC graph clearly showed that temporal feature set and SGLCM feature set are the top two. Though the result of SGLCM feature set in pre-contrasted phase is a little better than temporal feature set, Temporal feature set is still selected as the optimal features because of three reasons: Firstly, SGCLM features is greatly depending on the pixel value relative position, which means it sensitive to the quality of ROI extracted. And the quality of ROI is hard to guarantee. Secondly, SGCLM feature set cost a lot of computing resources. That feature set is made up of by 32 different feature scalars. Calculating each of scalar components means a lot of matrix computation. Finally, according to the pathological characteristic of cyst previous mentioned, its enhancement pattern makes itself a perfect candidate for temporal features.

The statistics in the tables reveal that only 33.3% (4/12) of all the best classification accuracy is achieved using the pre-contrasted CT images, which is currently widely used as the mainstream image medium for liver CAD[3][4][5][6]. Enhanced CT abdominal images of arterial phase and portal venous phase's ability in diagnosing the liver lesions have already been pathologically proven, for the effect of enhancing the pathological pattern of lesions. Also this feature could also be observed in this liver CAD approach, 66.7% of the best accuracy is obtained in those two phases. From above, we can see that multi-phase CT images do contain much more information than original non-enhanced CT images, which makes it a better choice in liver CAD approach.

Future works will include semi-automatic lesion ROI determination using several mathematical approaches. The advantage of using enhanced CT images will be further explored, other kind of features will be extracted (e.g. the relationship of texture features currently extracted on different phase of CT images). Furthermore, other machine learning classifier will be used, and their performance will be compared.

TABLE I. FOS FEATURE SET PERFORMANCE (CV ACCURACY)

Phase	**Class**		
	Normal vs. Abnormal	***Cyst vs. Other disease***	***Haemangioma vs. carcinoma***
Pre-contrasted	0.8933	0.923	0.5484
Arterial	0.8667	0.9744	0.8621

Phase	Class		
	Normal vs. Abnormal	***Cyst vs. Other disease***	***Haemangioma vs. carcinoma***
Portal venous	0.96	0.9487	0.8387
Delayed	0.8267	0.9487	0.7586

TABLE II. SGLCM FEATURE SET PERFORMANCE (CV ACCURACY)

Phase	Class		
	Normal vs. Abnormal	***Cyst vs. Other disease***	***Haemangioma vs. carcinoma***
Pre-Contrasted	0.92	0.9744	0.5806
Arterial	0.7333	0.9744	0.8387
Portal venous	0.8533	0.9744	0.8387
Delayed	0.7867	0.9744	0.7097

TABLE III. REDUCED SGLCM FATURE SET PERFORMANCE (CV ACCURACY)

Phase	Class		
	Normal vs. Abnormal	***Cyst vs. Other disease***	***Haemangioma vs. carcinoma***
Pre-Contrasted	0.9041	0.973	0.5517
Arterial	0.7945	0.973	0.8621
Portal venous	0.8767	0.973	0.931
Delayed	0.8082	0.9729	0.7241

TABLE IV. REDUCED FULL FEATURE SET PERFORMANCE (CV ACCURACY)

Phase	Class		
	Normal vs. Abnormal	***Cyst vs. Other disease***	***Haemangioma vs. carcinoma***
Pre-Contrasted	0.9242	0.9714	0.8929
Arterial	0.909	0.9714	0.9643
Portal venous	0.9545	0.9729	0.9643
Delayed	0.8939	0.9714	0.8929

TABLE V. TEMPORAL FEATURE SET PERFORMANCE (CV ACCURACY)

Class	**Accuracy**
Normal vs. Abnormal	0.9552
Cyst vs. Other disease	0.9722
Haemangioma vs. carcinoma	0.9

IV. CONCLUSION

In the current study, the texture-based features and temporal features are used to compose the feature vector has the best classification accuracy using portal venous phase of enhanced CT images. The classification accuracy is 0.955, 0.972and 0.964 for normal-abnormal, cyst-otherdisease and carcinoma-haemangioma sub problems respectively.

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