IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331
PP 06-11
www.iosrjournals.org

Detection of hepatocellular carcinoma using a new approach in multi-resolution analysis of CT images

Sreeja P, Hariharan S
[1](Dept. of Electrical Engineering, College of Engineering, Trivandrum, India)
[2](Dept. of Electrical Engineering, College of Engineering, Trivandrum, India)

Abstract: *This paper présents a new technique of multi-resolution analysis of CT images of primary liver cancer. The ripplet transform acts as an efficient multi scale geometric analysis tool for digital images. Its potential towards the image denoising, image compression and image restoration are an emerging research area of image processing and pattern recognition. In this work the role of ripplet transform type II in the domain of feature extraction and classification are examined. The coefficients of ripplet transform directly and statistical features and GLCM features of the transformed domain are extracted and applied to the machine learning algorithm and estimated the accuracy. The classification matches with the labelling done by an experienced radiologist.*

Keywords: *Classification accuracy, features , Ripplet Transform, Singularity*

I. Introduction

Efficient représentation and extraction of relèvent features play a vital role in the image compression and classification, especially in the case of médical images. Texture analysis of medical images is an on going research area for the past several years. Its application extends from the segmentation of organs, detection of healthy and pathological tissue to the classification with help of advanced machine learning algorithms.Texture represents the coarseness, smoothness and regularity of the image. Texture analysis has been carried out in structural, spectral, model based and transform based methods. In transform based methods fourier analysis is the important and earlier mthod. In this the signal is represented by the weighted sum of basis function. These wights are called coeffients. Mapping from the inputs to coeffiecients is called transform. Smooth images can be efficiently represented by Fourier transform. Edges or boundaries in an images causes discontinuities. These discontinuities are called singularities. Fourier transform fails to represent the one dimensional (1D) periodic singularity. Even though wavelet transform represents the 1D singularty, it fails to resolve 2D singularity along arbitarily shaped curves. This is because of the fact that the wavelet transform is just a tensor product of two 1D wavelet transform along horizontal and vertical singularities. To overcome the limitation of wavelet Ridgelet was introduced which is based on Radon transform. It is capable of extracting lines of arbitrary orientations. To resolve 2D singularty along smooth curves curvelet transform based on multiscale ridgelet was proposed. To generalize the parabolic scaling law of curvelet Jun Xu *et al* proposed the Ripplet transform. The Ripplet I transform acheves the anisotropic directionality with the introduction of two parameters, i.e. support c and degree d. The curvelet transform becomes a special case of Ripplet I with c=1and d=2[1].

On the basis of generalized Radon transform Jun Xu *et al* again proposed Ripplet transform Type II (ripplet II). It uses the generalized Radon transform to convert singularities along curves into point singularities in generalized Radon domain and then uses wavelet transform to resolve this point singularities. Sparser representationof 2D images can be well achieved with ripplet II transform. This helps to efficient representation of edges and textures. In [2] the authors have developed the forward and inverse ripplet transform Type II for continuous and descrete signnals. Texture feature extraction, edge detection, image retrieval and classification using ripplet II have been demonstated. The rotation invariant property of the transform has also experimantally proven which is useful for texture classification [2] . Multi resolution texture analysis of different organs from CT images has been adressed in [3] by L. Dettori *et al.* A comparative analysis of texture classification algorithm with five sets of wavelets, ridgelet and curvelet based feature vectors has been presented. Conventional texture classification algorithm based on gray level co-occurance and run length method also applied to verify the results [3]. Chi-Chang Chen *et al* used fractal feature analysis for the classification of medical images. The degree of randomness associated with medical images was enhanced with natural random structure and the random noise imposed on it. This made helpful to apply the fractal features in connection with fractional Brownian motion to classify the normal and abnormal liver tissue. In this work direction properties were not considered [4].

In wavelet transform based texture analysis the image is decomposed into low frequency and high frequency sub bands and statistical features such as mean, standard deviation etc are computed from these sub bands and are used as features for classification. Wavelets are good in detecting point singularities, but not performing well along smooth curves. To overcome this difficulty Ridglet transform was proposed. Texture classification using Ridgelet transform was presented by S. Arivazhagan *et al*. In this work ridgelet transform was applied to a set of texture images. In addition to statistical features, GLCM features also extracted from the ridgelet coefficients to improve the classification accuracy [5]. Chung-Ming Wu *et al* have proposed multi resolution imagery and fractional Brownian motion model for the classification of liver tissue into normal, hepatoma and cirrhotic using Bayesian classifier, The work is compared with conventional texture features from SGLDM and laws of texture energy measures [6].The wavelet transformed coefficients of approximation and detailed images are used as the feature input of the probabilistic neural network classifier to discriminate normal liver from fatty liver of ultra sonography images. Non-separable Gabor wavelets are used for the discrimination of normal liver from hepatitic and cirrhotic liver which yield better results. The result was compared with conventional dyadic wavelets and statistical methods of feature extraction [7] [11][12] [13]. Ripplet transform is a new approach in signal and image processing which can be applied to image compression, image denoising, and pattern classification. In the proposed work features extracted from ripplet type II transform are used to classify the CT liver images into normal and hepatocellular carcinoma. For improving the classification accuracy the gray level co-occurance matrix (GLCM) features are deduced from the transform coefficients [9]. The algorithm provides better classification results.

II. Materials And Method

1. Multiresolution Analysis from Wavelet to Ripplet

Texture analysis of image plays a vital role in the image processing and pattern recognition systems. In the case of medical radiology images the shape features contributes significantly less compared to texture. Conventional texture analysis is carried with statistical features and gray level co-occurance and run length matrices. On mapping to frequency domain the Fourier transform fails to detect the edge and line singularities. Multi channel texture analysis including wavelets and Gabor used widely for texture classification. The non-orthogonal property of Gabor features causes significant correlation between texture features and hence leads misclassification[11].Wavelet transform has extensively used for texture classification. The image is decomposed using wavelet transform and statistical features are extracted from the approximation and details of the transformed sub-images. The good performance of wavelet in one dimension cannot be achieved in 2D because of the fact that the wavelet transform in 2D is the tensor product of 1D transform. The wavelet transform work well in detecting edges but fails to detect smooth edges.

To improve the performance of wavelet in 2D Candes and Donoho proposed a new system of representation called Ridgelet transform. It can efficiently represent line singularities. This is done by converting the line singularity into point singularity by mapping it into the Radon domain. This point singularity can be effectively resolved by the wavelet transform. Ridgelet transform provides information along radial orientation along linear edges in image[8][16] Since the ridgelet is also not able to represent 2D singularities Candes and Donoho again proposed first generation curvelet transform followed by second generation. Anisotropic directionality can be achieved by curvelet transform based on parabolic scaling law and thereby resolved the discontinuity along smooth curves. The generalization of optimal parabolic scaling law of curvelet transform led to the development of Ripplet transform. The type I Ripplet transform introduced two parameters support *c* and degree *d* to generalize curvelet transform which made the curvelet transform a special case of ripplet transform Type I with c=1 and d=2.These parameters provide anisotropic property to the ripplet transform for representing singularity along arbitrary shaped curves. In addition to the features of high directionality, general scaling and support, multi-resolution capability and anisotropic property, the ripplet transform has good localization and fast coefficient decay. The fast coefficient decay provides higher energy concentration ability to the transform [1].

2. The Ripplet Transform

Similar to definitions of wavelet and curvelet, the Ripplet function can be generated from the ripplet element function,

$$\rho_{a\vec{b}\theta}(\vec{X}) = \rho_{a\vec{0}0}(R_\theta(\vec{X}-\vec{b})) \qquad (1)$$

where R_θ is the rotation matrix given by

$$R_\theta = \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix}. \qquad (2)$$

The ripplet function is named because of its ripple like nature in spatial domain. In frequency domain this element function can be represented as

$$\rho_a(r,\omega) = \frac{1}{\sqrt{c}} a^{\frac{1+d}{2d}} W(a,r) V\left(\frac{a^{\frac{1}{d}}}{c.a}.\omega\right) \tag{3}$$

where $\rho_a(r,\omega)$ is the Fourier transform of $\rho_{a\vec{0}0}$. *W(r)* is the radial window on [1/2, 2] and *V(ω)* is the angular window on [-1,1] which follow the admissibility conditions

$$\sum_{j=0}^{+\infty} \left|W(2^{-j}.r)\right|^2 = 1 \tag{4}$$

and

$$\sum_{l=-\infty}^{+\infty} \left|V\left(\frac{1}{c}.2^{-\left\lfloor j\left(1-\frac{1}{d}\right)\right\rfloor}.\omega - l\right)\right|^2 = 1 \tag{5}$$

As discussed earlier, c determines the support of ripplets and d defines the degree of ripplets. The effective region of ripplet function is an ellipse with major axis pointing in the direction of ripplets. The major axis represents the effective length and the minor axis represents the effective width. The length and width of the effective region holds the relation $width \approx c \times length^d$. The most distinctive property of ripplets is the general scaling which is achieved by tuning the support c and degree d. With d=1 the ripplets will not have anisotropic property. With d>1, the ripplets obtain anisotropic property and becomes capable of capturing singularities along any arbitrary directions.

For a 2D integrable function $f(\vec{x})$, the continuous ripplet transform is defined as the inner product of $f(\vec{x})$ and ripplets.

$$R(a,\vec{b},\theta) = \langle f, \rho_{a\vec{b}\theta}\rangle = \int f(\vec{x})\overline{\rho_{a\vec{b}\theta}(\vec{x})}d\vec{x} \tag{6}$$

When the ripplet function intersects with curves in images the corresponding ripplet coefficients $R(a,\vec{b},\theta)$ will have large magnitudes and these coefficients decay along the direction of singularity as a →0.

Digital image processing needs discrete transform. For discretizing the continuous transform the parameters of ripplets are to be discretized. The scale parameter *a* is to be sampled at dyadic intervals and position parameter *b* and rotation parameter *θ* are sampled at equally spaced intervals which are substituted with discrete parameters a_j, $\vec{b}_k$ and θ_l satisfying that $a_j=2^{-j}$, $\vec{b}_k=[c.\ 2^{-j}.k_1,\ c.\ 2^{-j/d}.k_2]$ and $\theta_l = \frac{2\pi}{c} 2^{-\lfloor j(1-1/d)\rfloor}.l$ where $\vec{k} = [k_1 \quad k_2]^T$, $(.)^T$ denotes the transpose of a matrix and $j, k_1, k_2, l \in Z$. The degree of ripplets can take any value from R. The support c controls the number of directions in high pass band and degree d determines the number of directions that changes across band. The discrete ripplet transform of an $m \times n$ image $f(x,y)$ is given below,

$$R_{j,\vec{k},l} = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\overline{\rho_{j,\vec{k},l}(x,y)} \tag{7}$$

where $R_{j,\vec{k},l}$ is the ripplet coefficients.

III. Methodology

The work is intended to discriminate the primary liver cancer, hepatocellular carcinoma, from normal liver tissue. This classification algorithm consists of three main parts namely the segmentation of the normal and cancerous tissue, extraction of relevant features from the transformed domain and classification of the features into different classes with the help of a suitable binary classifier.

1. Data set and Segmentation

The data set consists of abdominal CT images of normal liver and liver with hepatocellular carcinoma. The region of interest is identified by an experienced radiologist. Initial phase of the work consists of the segmentation of the liver from the abdominal CT images. Conventional morphological operation together with thresholding is used for segmenting the liver from the neighboring organs. From the segmented liver both normal and abnormal tissue portion is identified by the radiologist and are cropped with the help of interactive cropping tool of Matlab and saved. This final data set consists of 30 images normal liver tissue and 30 HCC images. Fig 1.1 and fig1.2 shows abdominal CT image and segmented liver portion . The cropped portion of normal liver tissue and HCC which are used as data set are shown in Fig1.3 and Fig 1.4 respectively.

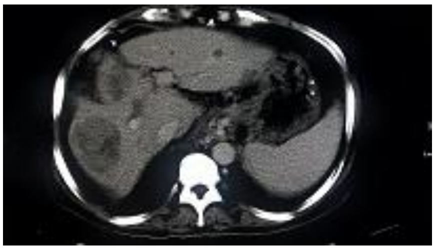

Fig1.1 Liver CT image

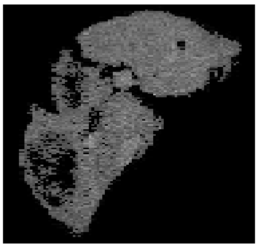

Fig1.2 Segmented liver

Fig1.3 Normal liver tissue

Fig1.4 HCC

2. Feature Extraction

After completing the segmentation work the cropped images are resized into uniform size. This is done to make the extracted features suitable for applying to the classifier. As explained in the introduction, statistical features and GLCM features usually have been extracted in the case of textural analysis in spatial domain. In frequency domain features extracted from the coefficients of wavelet, gabor and ridgelet transforms are the main counter parts. But it has been proved that the features based ripplet transform coefficients perform better for the texture analysis.This acts as a motivating factor to apply Ripplet transform Type II for extracting the features from the normal and HCC tissue.

***Feature Extractor I*:** In the initial phase the image is mapped into ripplet domain. For finding the transform Daubechies wavelet db 4 and degree 3 is used since it gives optimal result. The ripplet II coefficients are extracted by finding the ripplet transform of the segmented portion of the image. The gray level co-occurrence matrix has been determined. The statistical features mean, variance, standard deviation, correlation, contrast, energy, entropy, inverse difference moment, root means square value, skewness, kurtosis, smoothness and homogeneity of the GLCM have been computed. These statistical features are fed to the input of the classification algorithm.

***Feature Extractor II* :** Decompose a given image with discrete wavelet transform into 3 subimages. The GLCM of the subimage and its statistical features are computed. Thirteen statistical features listed above have been extracted and used ans the input features of the classifier.

3. Classification Algorithm

Support Vector Machines (SVM) are supervised non probabilistic supervised learning model used for classification and regression. In SVM the features are marked as points in the feature space. The points belonging to different classes are separated by a decision boundary which is a straight line for the case of linear binary classifiers. The features which determine the decision boundary is called as the *support vectors*. Nonlinear classification can also be done by SVM by using kernel trick that maps the features into high dimensional features space. Some common kernels are polynomial, Gaussian, radial basis and hyperbolic tangent. SVM requires full labeling of the data [10]. In this work SVM is used as the classifier.

4. Results and Discussions

The images of normal liver and HCC were transformed into ripplet domain. The features have been extracted from each transformed image with the help of the feature extractor I and II. These features were applied separately to the SVM and predicted the accuracy. Thirty images each of normal liver and HCC are used training and testing. 10-fold cross validation is used for prediction. The accuracy of the classifier is checked with linear kernel and RBF kernel. The results are tabulated in Table 1. It has been seen that SVM with RBF kernel performs better with features extracted from Ripplet transform domain. The classification accuracy is 97.5% .

Table 1 Variation of accuracy with RT and DWT

SVM Kernel	**Accuracy with Features Extracted with**	
	Ripplet Transform	Discrete Wavelet Transform
Linear	0.95	0.95
RBF	0.975	0.95

The accuracy of classification has been estimated by applying individual features. A graph is plotted which shows the variation in accuracy while applying individual features. The graph is shown in fig 1.5. From the graph it is obvious that the individual features perform better in ripplet transform domain.

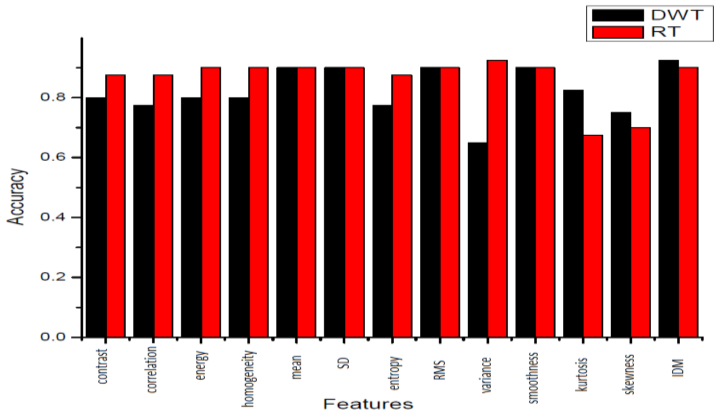

Fig 1.5 Variation of accuracy for different features

IV. Conclusion

In this paper the recently proposed RippletII transform has been used for detecting hepatocellular carcinoma from abdominal liver CT image .For this the region of interest was initially mapped into Ripplet transfom domain and GLCM was determined. Various statistical features were extracted from normal liver tissue and HCC portion of the CT image. The same computation was carried out for the wavelet decomposed sub-images also. These features applied separately to SVM and the accuracy of classification was determined. Both the classifiers yield better classification accuracy. But RBF kernel SVM applied with RippletII- GLCM statistical textural features provided best classification accuracy of 97.5%.

The work can be extended by extracting more relevant features in spatial domain, frequency domain and ripplet domain to efficiently discriminate different liver lesions from abdominal CT images.

Acknowledgements

Authors acknowledge the experienced radiologists from different hospitals at Trivandrum for providing labeled CT images for both normal liver and hepatocellular carcinoma.

References

Journal Papers:

[1]. J. Xu, L. Yang and D. O. Wu, “Ripplet: A new transform for image processing”, *Journal of Visual Communication and Image Representation*, 21(7):627-639, 2010.

[2]. Xu, J., and D. Wu. "Ripplet transform type II transform for feature extraction." *IET image processing* 6.4 (2012): 374-385.

[3]. Dettori L., and Semler L., “A comparison of wavelet, ridgelet, and curvelet-based texture classification algorithms in computed tomography*,” Elsevier, Comput. Biol. Med.. 37, (4),* 486 –498 (2007).

[4]. C.C Chen, J.S Daponte, M.D Fox,“Fractal feature analysis and classification in medical imaging*” ,IEEE Trans. Med. Imaging, 8* (1989), pp. 133–142

[5]. S. Arivazhagan a, L. Ganesan b, T.G. Subash Kumar, “Texture classification using ridgelet transform”, *Elsevier, Pattern Recognition Letters,* June,2006

[6]. Chung-Ming Wu, Yung-Chang Chen, “Texture Features for Classification of Ultrasonic Liver Images”, *IEEE Transactions on Medical Iimaging, vol. 11, no. 2,* June 1992

[7]. Aleksandra Mojsilovi ,Miodrag Popovi´, Srdjan Markovi, and Miodrag Krsti, “Characterization of Visually Similar Diffuse Diseases from B-Scan Liver Images Using Nonseparable Wavelet Transform”, *IEEE Transactions on Medical Imaging, vol. 17, no. 4,August 1998*

[8]. J L Strack, E J Candes,, D L Donoho, “The curvelet Transform for image denoising”, *IEEE Transaction for Image Processing,Nov,2002*

Books:

[9]. Gonzalez and Woods, “Digital Image Processing”, Pearson Education

[10]. Ethem Alpaydin, “Introduction to Machine Learning”, PHI

Theses:

[11]. D.S. Chan, *Theory and implementation of multidimensional discrete systems for signal processing*, doctoral diss., Massachusetts Institute of Technology, Cambridge, MA, 1978.

Proceedings Papers:

[12]. A. Ahmadian, A. Mostafa, , M. D. Abolhassani, Y. Salimpour, “A texture classification method for diffused liver diseases using Gabor wavelets”, *Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China*, September 1-4, 2005

[13]. Yali Huang, Lanxun Wang, Caixia Li, “Texture Analysis of Ultrasonic Liver Image Based on Wavelet Transform and Probabilistic Neural Network” , *IEEE International Conference on BioMedical Engineering and Informatics,2008*

[14]. Ayşe Elif Öztürk, Murat Ceylan, Ali Sami Kıvrak, *“A New Approach for Liver Classification Using Ridgelet / Ripplet-II Transforms, Feature Groups and ANN”*, IFMBE proceedings · September 2014

[15]. Tayebe Muhammady , Hassan Ghassemian “Using Co-occurrence Features Extracted From Ripplet I Transform in Texture Classification”, *ICEE 2012*

[16]. D L Donoho, M R Duncan , “Digital Curvelet : Strategy, implementation and experiments”, proc. Aerosense 2000,Wavelet Applications VII, SPIE, Vol 4056