Texture analysis for liver segmentation and classification: a survey

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***Abstract*— Texture is a combination of repeated patterns with regular/irregular frequency. It can only be visualized but hard to describe in words. Liver structure exhibit similar behavior; it has maximum disparity in intensity texture inside and along boundary which serves as a major problem in its segmentation and classification. Problem gets more complicated when one applies simple segmentation techniques without considering variation in intensity texture. The problem of representing liver texture is solved by encoding it in terms of certain parameters for texture analysis. Numerous textural analysis techniques have been devised for liver classification over the years some of which work equally work well for most of the imaging modalities. Here, we attempt to summarize the efficacy of textural analysis techniques devised for Computed Tomography (CT), Ultrasound and some other imaging modalities like Magnetic Resonance Imaging (MRI), in terms of well-known performance metrics.**

Keywords – Texture Analysis; Liver Classification; CT; MRI; Ultrasound

I. INTRODUCTION

Liver is the largest organ of body and is located in the upper left of abdomen. Some important functions of liver include metabolizing drugs, clearing toxins from the blood, and producing blood proteins and bile to aid digestion. On the other hand, it has to put up with some deadly diseases like hepatitis, cysts, tumor etc. Liver images have various granular structures called texture. Normal liver usually differs with the diseased one in terms of intensity texture. This variation helps in determining the corresponding disease.

A Computer-Aided-System (CAD) is a merger of medical imaging and tissue characterization techniques, and is widely used in liver diagnosis. CAD systems are not the replacement for doctors rather they only provide a second opinion during diagnosis and strengthen practitioners' judgment about disease.

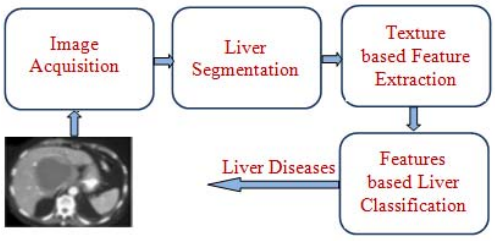

Figure 1. Top Level Layout of Liver CAD System

A typical CAD system segments liver from image, computes texture based features from segmented liver and finally, classifies liver into predefined classes of diseases. Feature extraction and liver classification steps of CAD heavily rely on segmentation accuracy. Inaccurate segmentation definitely corrupts the following steps. Several factors which make liver segmentation and classification very hard include variation in intensity texture inside and along liver boundary, bad contrast, least variability between intensity values of lesion and its surrounding area, image noise and liver geometry between patients. These factors must be taken care of while proposing any feature based liver classification method.

Rest of the paper is categorized as follows. Section 2 presents an overview of several texture features and texture measure methods. Section 3 provides detailed information on different texture analysis techniques that have been used for liver classification. Section 4 supplies performance review of these techniques whereas section 5 concludes the paper.

II. TEXTURE MEASURE FEATURES AND TECHNIQUES

Several textural analysis techniques have been proposed to extract useful features for reliable liver tissue classification. Some extensively used techniques are:

- Gray Level Difference Statistics (GLDS): GLDS is the Probability Density Function (PDF) of pair pixels lying at specific distance and having a particular intensity value difference. Inter pixel gray level values have large variation for fine texture and least variation for coarse texture.
- Spatial Gray level Dependence Matrices (SGLDM): SGLDM [1] exploits the fact that spatial relationship between gray levels of an image contributes to overall texture properties of the image. It computes matrix by counting how many times pixels with intensity i and j occur at specified offset.
- Gray level Run length Statistics (RUNL): RUNL [2] makes use of the fact that there are consecutive points in image having same gray level along a particular direction. Coarse texture contains relatively long runs than short runs. Opposite is true for fine texture.
- Gray Level Histogram: It employs intensity distribution of image to find out texture parameters.
- Edge Frequency based Texture Features: These features are inversely related to the autocorrelation function and are based on distance related gradient. Micro-edges and macro-edges can be detected using small and large distance operator respectively.

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- First Order Parameters (FOP): These are independent of spatial relation between pixels and describe only echogenicity and diffuse variation characteristics.
- Laws Texture Energy Measure (TEM): TEM [3] uses convolution masks of 5x5 to detect various texture types. It works on five basic 1D masks convolved to produce 25 2D masks. Texture image is then filtered with these masks to extract useful features.
- Fourier Power Spectrum (FPS): This technique is useful for regular wave like patterns with a constant interval. Fourier transformation provides direction and frequency of pattern.
- Wavelet Features: These features are derived from wavelet transform of the image or Region of Interst (ROI). Major types are quincunx, Gabor and dyadic.

Selection of appropriate textural features plays an important role in success of above mentioned textural analysis schemes. Some important textural features include: Entropy (ENT), Local Homogeneity (LH), Gray Level Distribution (GLD), Run Length Distribution (RLD), Angular Second Moment (ASM), Contrast (CO), Correlation (CORR), Variance (VAR), Inverse Difference Moment (IDM), Standard Deviation (SD), Energy (E), Homogeneity (H), Uniformity (U), Sum Entropy (SENT), Mean (M), Short Run Emphasis (SRE), and Dissimilarity (D).

III. Literature Review

Out of several liver imaging modalities, ultrasound is the least expensive but less precise tool for detecting liver abnormalities. Conversely, CT scan is the most reliable but at the same time costly method of diagnosing liver diseases. A lot of liver texture analysis techniques have been proposed in the past with major focus on Ultrasound and CT imaging modalities. Some of these techniques have been evaluated [4] in past but in separate papers. Our study, contrary to previous studies, investigates the accuracy of these techniques in a single place. Following text elaborates these techniques.

A. CT Texture Analysis Techniques

A considerable percentage of liver texture analysis techniques are based on CT data. Many authors have put their efforts in evaluating and deriving useful information from CT liver images. Mir et al., in their work [5], characterized CT liver images into normal, visible and invisible malignancy. Their approach was based only on an insightful observation of features extracted using SGLDM, RUNL and GLDS. Twenty CT images from each class were used for computing an average value of features by aforementioned techniques. A keen observation revealed that features of ENT, LH and GLD play their discrimination role.

Mougiakakou et al. [6] amalgamated several feature extractors and NN classifiers for classifying CT liver images into normal, hepatic cyst, hemangioma, and HepatoCellular Carcinoma (HCC). FOP, SGLDM, GLDS, TEM and FDTA were used for feature extraction from ROI. Dimensionality of feature vector was reduced using Genetic Algorithm (GA) based on [7] because GA reduces features quite robustly [8]. 5 feature sets were given as input to the NN comprising of 5 individual NNs each of which was comprised of 4-class NNs and was trained by the back propagation algorithm. Learning rate and momentum were adaptive. Majority voting and weighted voting were used to combine the outputs of individual NNs in order to decide about final liver class.

Mala et al. work was a major effort to recognize diffused liver diseases. For this purpose, they developed an automatic liver segmentation and classification system [9] using CT scan data. First step was to apply morphological operations of closing, opening and then adaptive thresholding. Second step was complementing the image followed by multiplying the complemented image with original one to segment liver. Third step was to use orthogonal wavelet transform to compute horizontal, vertical and diagonal details. Details were further utilized to calculate eighteen textural features such as M, SD, ASM, CO, E and ENT for the distance of 4 pixels. Finally, they used features for Probabilistic Neural Network (PNN) training and classification. Mala et al. further extended their work [9] and proposed a new scheme [10]. They classified benign and malignant tumor using CT data by amalgamating biorthogonal wavelet transform with Linear Vector Quantization (LVQ) network. After initial preprocessing, image was complemented and multiplied with the original image to segment liver. Then FCM clustering was applied to divide image into liver, background and tumor. In classification, first step was to extract horizontal, vertical and diagonal coefficients using biorthogonal wavelet transform on tumor region. Second step was to build a Co-occurrence matrix that in turn was used for calculating second order statistical texture features such as ASM, CO, H and ENT in horizontal, vertical and diagonal directions using pixel distance of 1. These features were used for training LVQ neural network [11]. Experiments revealed optimized number of epochs, hidden neuron and learning rate parameter to be 100, 20 and 0.01 respectively.

Ioannis et al. [12] employed non-enhanced CT liver images to classify ROI into hemangioma, cyst, HCC, and normal types. They extracted distinct features of CT liver images using FOP, SGLDM, GLDS, FDTA and TEM. The reduced feature set based on GA was then fed to a feed forward neural network for classification. To achieve results, authors calculated the area under Receiver Operating Characteristics (ROC) curve (A_z) both for multiclass and one-versus-all discriminations. Results showed that FOP features produced superior results (mean $A_z = 0.802$). During same time period, Bharathi et al. [13] utilized the better feature representation capability and least information redundancy of Zernike moments and Legendre moments for classification of normal and HCC liver using CT images. Total 200 ROI were used out of which 140 belong to healthy liver class and 60 to HCC. Each ROI was further segmented into multiple 8x8 segments out of which 75 were used for training and the remaining for testing. The classification efficiency using Zernike features was 92.37% with 5% noise, 85.50% for 10 % noise and 77.86% for 15 % noise. The classification result with Zernike and Legendre feature vector for normal liver was 98.60 % and 97.57%, whereas that for HCC was 90.00% and 80.25%.

Sobia et al. [14] proposed an SVM based solution for discriminating hemangioma, hepatoma, cirrhosis and normal

liver. Initially, they segmented liver from CT images using snakes algorithm and obtained ROI, from which features were extracted using SGLDM. Then, feature set was given as input to a hierarchical SVM that was designed to discriminate between diseased and non-diseased tissue. Diseased image was then fed to another SVM that was designed to characterize it as hemangioma or non-hemangioma. Non-hemangioma image was further used by final SVM to classify it between hepatoma and cirrhosis. Overall classification accuracy of the method was 77%.

Authors of [15] proposed an automatic liver segmentation method by using pixel based feature extraction, SVM based classification and morphological operations. Wavelet transform [16] was used for feature extraction instead of Fourier [17] and Gabor [18] because it represents texture at multiple scales. Pixel based features thus obtained serve as input to SVM classifier. SVM based classification does not cater spatial information and second, it heavily misclassifies pixels. To avoid these problems, well-chosen morphological operations were used in sequence: 1) dilation and erosion with square structuring element six pixels wide, 2) removing areas other than largest, 3) hole filling, 4) removing spurs, and finally 5) erosion and dilation.

Wu et al. proposed a novel approach [19] based on statistical moments for texture analysis. They evaluated Legendre, Zernike, Krawtchouk and chebichef moments [20,21,22] for texture feature extraction in local neighborhood of each pixel. After proving discrimination capability of these moments for standard Brodatz textures, they were applied on CT liver images for tumor recognition. The texture features, calculated using aforementioned moments, for multiphase CT liver images were classified using SVM. Krawtchouk moments were best in terms of classification accuracy.

B. Ultrasound Texture Analysis Techniques

Texture analysis of liver ultrasonics has always been a source of fascination for researchers. Many well-known liver texture analysis techniques, proposed by researchers, are based on ultrasound images. Pavlopoulos et al. have investigated the usefulness of GLDS and FDTA (based on Fractal Brownian Motion theory [23]) for ultrasound liver classification in their research work [24]. Liver images were categorized into normal, hepatoma and cirrhosis types using 32x32 pixels rectangular Region of Interest (ROI), which was manually demarcated by expert physicians. Results, collected using the three common imaging modalities i.e. CT, MRI and Ultrasound, were quite encouraging. Strive for better classification mechanism continued and during same time period, Bleck et al. have devised a novel texture analysis method [25] based upon an Auto Regressive Periodic Random Field Models (APRFM) [26]. They compared features obtained using APRFM with Conventional Texture Analysis (CTA) techniques, based upon previous such comparative studies [27, 28]. In APRFM, main optimization problem of deciding neighborhood was solved.

Wavelet features are also widely used for ultrasound liver image classification such as Mojsilovik et al. used 6-level quincunx wavelet decomposition for identifying diffused liver diseases in their work [29]. Algorithm was designed to estimate channel variances at the output of each filter of the filter bank. Variance estimate was then used for texture based liver classification. This scheme was effective as well as simple.

Kyriacou et al. used GLDS, RUNL, SGLDM and FDTA for classification of diffused liver diseases using ultrasonic images in their research work [30]. They computed ENT and ASM in GLDS; GLD and RLD in RUNL whereas SENT, CO, CORR, VAR and ENT in SGLDM. FDTA was based upon a non stationary stochastic process described by fractional dimension. Parameters so extracted were used in KNN classification. They further investigated the accuracy of these techniques with the addition of FOP [31]. Motivation was to increase the accuracy which was previously 70% [32, 33]. They derived FOP parameters – M and VAR - from the PDF. Further, they used SRE and GLD from RUNL category; ASM, ENT and CO under GLDS category whereas IDM and SENT under SGLDM category. Feature extraction was followed by 3-step KNN classification.

Pavlopoulos et al. also characterized diffused liver diseases automatically using Fuzzy Neural Network (FNN) [34]. 12 texture features for classification were extracted using FDTA, SGLDM, GLDS, RUNL, and FOP. These features were further reduced to 6 using different feature combinations. Then voronoi diagram of training patterns was constructed which was used by FNN to generate fuzzy sets and built class boundaries in a statistical manner. For validation, authors used 150 liver images and showed 82.67% classification accuracy.

Guohui et al. work [35] is based on feature extraction both from M-mode motion curve of liver and B-mode ultrasound liver image. They extracted 25 features through FOP, RUNL, GLDS, and a few other unique features using M-mode motion curve. After feature extraction, they applied fisher linear decision rule for selecting 20 useful features based on minimum classification error. Experimental results revealed that features obtained using motion curve were more suitable for discriminating normal or cirrhosis liver in terms of sensitivity and specificity. Guitao et al. proposed another method [36] for ultrasound liver images classification. For feature extraction they used FDTA and SGLDM on 64x64 pixels sub-image. The joint feature vector, thus obtained, was used to discriminate 273 healthy and 99 fibrosis liver images. Two classification methods - Fisher linear classifier and SVM (leave-one-out algorithm) - were used. Both classifiers were good in terms of classification rate. However, the joint feature vector proved to be a bit better.

Ahmadian et al. proposed a scheme [37] to identify diffused liver diseases using Gabor wavelet and classified ultrasonic liver image into normal, cirrhosis and hepatitis classes. They exploited three well known benefits of Gabor wavelets i.e. maximum joint space frequency resolution, smaller feature vector, and invariance to shift of image contents. Features were extracted and images were classified into different categories using dyadic wavelet transform, Gabor wavelet transform and statistical moments and features.

In [38], ultrasound liver image was decomposed into sub images and SGLD matrices were calculated for each sub-image. This study was much similar to [39]. A total of 100 matrices were computed for sub images, and seven feature

descriptors were calculated from each such matrix. Feature descriptor was composed of element difference moment of order, inverse element difference moment of order, U, ENT, H, and CO. Feature vector was used as input to Self Organizing Map (SOM). After NN convergence, neurons were plotted in the weight space. No common area between fatty and normal liver plots proved good discriminating power.

Balasubramanian et al. [40] automatically classified benign, malignant, cyst and normal liver images using texture features computed through SGLDM, RUNL, TEM and Gabor wavelets. Eight features were chosen from manually selected features and Principle Component Analysis (PCA) based optimal features. PCA based features were used by K-means clustering algorithm, whereas manually selected features were classified by BPN. It seems against intuition but classification results of BPN were better than K-means. Same liver diseases were classified by Poonguzhali et al. [41] study. They used TEM, Autocorrelation, Edge Frequency method and SGLDM for feature extraction from ROI of ultrasound images. PCA was used to select optimal feature set from extracted features. Optimal features were then used for K-means classification.

Authors of [42] have proposed a classification system for identifying normal and fatty liver ultrasound images using Discrete Wavelet Transform (DWT). Daubechies mother wavelet was chosen and three level decomposition of DWT was used. M and SD of approximation and detail sub-parts of three level decomposed images were used as feature parameters. To remove the redundant features out of a total of 24, the vertical and diagonal detail coefficients of 3-level DWT, the horizontal detail coefficient and approximation coefficient of 2-level DWT were used. PNN was used for classification. Input and output layers were in accordance with input features and the rule of competitive learning respectively.

Huang et al. used SGLDM, Gray level histogram and GLDS for textural analysis of liver in their experimental work [43]. Initially, image was de-noised and features were computed from ROI. Feature set included ASM and ENT for all, M for Gray level histogram and GLDS, CO for GLDS and SLDM, Homogeneity for SGLDM, and VAR for Gray level histogram only. Finally features were classified using PNN. SGLDM was also used by Kundu et al. [44] to perform texture analysis on 76 normal and 12 fatty liver ultrasound images. Images were denoised using Gaussian smoothing filter before feature extraction using SGLDM. These features were used as input to SOM [45] for examining the clusters formation of input data. Authors showed the result of clustering with and without Gaussian smoothing however classification results were better for Gaussian filtered image.

C. MR and Other Texture Analysis Techniques

MR and some other imaging modalities are less commonly used for liver texture analysis because it is quite difficult to extract useful texture information from the images corrupted by undesirable artifacts of these modalities.

Xuejun et al. [46] followed almost similar approach to that of [34], but crisp NN was employed instead of FNN. In their work, shape features were extracted from liver MR images by drawing two approximate straight lines from liver contour in the premises of ROI. The angle formed by these lines and the distance of their intersection from apex point were used as two shape features. Similarly, textural features like CO, ENT, ASM, M, IDM, SD and M were calculated using GLDS. Shape and texture features were concatenated and fed to a NN for classification. Output, greater than 0.5, indicated cirrhosis.

Shih et al. work [47] is based on biopsy liver images classification as HCC or normal liver using an improved Simpler PNN. They converted stained biopsy images to 8 bit gray level images using Ohta's transformation. Five versions of transformed gray level image were used. FDTA was used to compute a pair of FD estimators for each of five versions and Hotelling's T2 test was applied to select best FD features pair that was fed to the improved PNN. They showed that SPNN was better than the traditional Specht's PNN [48] in terms of simple architecture and faster recall for most network sizes.

Mohamed et al. proposed a bloc-wise clustering based technique [49] for extracting features of D, U, ENT, and CO, using SGLDM from mammograms in order to classify normal, benign and malignant tissues. Initially, image was enhanced using cropping and histogram equalization. Then features were extracted from fixed blocs of the image using SGLDM. Feature extraction methods were based either on pixel wise segmentation approach or ROI selection approach. PCA was then used for dimensionality reduction prior to using Fisher Linear Discriminant Analysis. Then, classification was performed with multiple classifiers however RBF was best.

IV. Discussion

Different authors have used different performance metrics to check classification accuracy. Some have used classification error/accuracy as a measure of performance while others have exploited area under ROC curve. Even some authors have validated their proposed schemes just by manual inspection performed by expert radiologists. A summary of classification results using different textural measures can be of substantial value for setting future directions. Such a result summary is presented in compact form in Figure 2. Horizontal axis shows textural analysis techniques used in different classification schemes whereas vertical axis represents classification accuracy of these techniques for different diseases. Another useful performance metric is specificity and sensitivity which is summarized in Table I. Table II depicts the textural features type, data type and number of data samples.

V. Conclusion

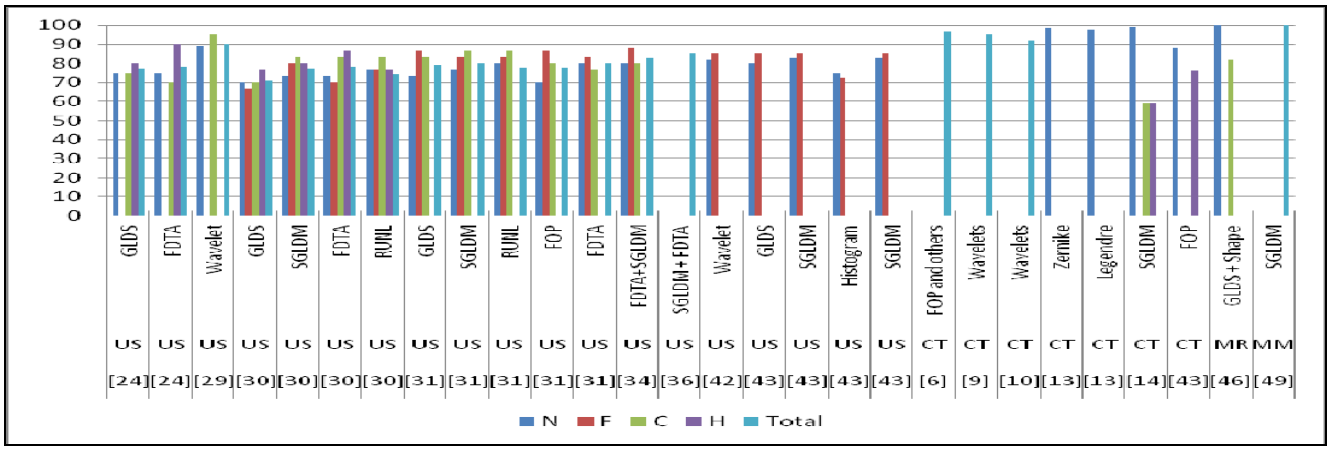
It has been observed that techniques based on CT texture analysis, though evaluated for a few liver diseases, have much better discriminating power than others. Contrary, methods employing ultrasound images have been used for diagnosing a large number of diseases but are less accurate. In case of CT scan, techniques based on statistical moments perform better such as [13], based on Legendre moments, is best in determining normal liver. For Ultrasound, wavelet-based techniques for feature extraction such as [29] outclass others.

This work is a modest beginning to summarize texture analysis methods for liver categorization that may further be

evolved to compare major texture measure techniques under identical environment each for MRI, CT and Ultrasound images. These schemes have exploited the variation in texture patterns of diseased and healthy liver. Even in the former case, liver texture varies from disease to disease thus serves as a distinguishing tool in subjective evaluation of various types of liver diseases based on echo texture and echogenicity. No texture measure method is perfect for each of three imaging modalities. Instead, their combination produces better results in certain applications.

VI. Future Work

Though our preliminary investigation is much promising, there is a lot more to be done. This research can further be extended into two directions. First, testing all texture measure methods using same data set and similar performance measures may provide a clearer view. Second, adding more texture measure methods can potentially provide better comparative study.



N = Normal, F = Fatty, C = Cirrhosis, H = Hepatoma, T = Total

Figure 2. Liver texture analysis results for individual disease types

TABLE I. Liver Texture Analysis Results (Sensitivity and Specificity)

	Data Type	Features	# of Samples	Accuracy				
			T	Sensitivity	Specificity	PPV	NPV	Accuracy
[9]	CT	Wavelets	100	96	94	94	96	95
[10]	CT	Wavelets	100	98	85	88	98	92
[49]	MAMMO	SGLDM	71	100	100	-	-	100
[36]	US	SGLDM, FDTA	372	94.9	81.3	-	-	85.2
[6]	CT	FOS,SGLDM, GLDM,TEM, and FDTA	32	-	-	-	-	97
[37]	US	Gabor Wavelet	135	85.5	78	-	-	-

NPV = Negative Predicting Value, PPV = Positive Predicting Value, T = Total

TABLE II. Data Samples and Feature Extarction Techniques for Texture Analysis

	Data	Features	Number of Samples							Data	Features	Number of Samples				
			N	F	C	H	Other	T				N	F	C	H	T
[29]	US	Wavelet	37	-	20	-	S(65)	122	[2]	US	GLDS, FDTA	20	-	20	20	60
[13]	CT	Zernike, Legendre	140	-	-	-	HC(60)	200	[5]	US	GLDS,FDTA,RUNL,SGLDM	30	30	30	30	120
[43]	US	GLDS, SGLDM, Histogram	50	50	-	-	-	100	[6]	US	GLDS,SGLDM,FDTA,RUNL,FOP	30	30	30	-	90
[14]	CT	SGLDM	16		25	25	M(25)	91	[7]	US	FDTA+SGLDM	50	50	50	-	150
[42]	US	Wavelet	-	-	-	-	-	100	[9]	MR	GLDS + Shape	7	-	11	-	18
[19]	CT	FOP	38	-	-	24	HC(20), Y(15)	97								

N = Normal, F = Fatty, C = Cirrhosis, H = Hepatoma, S = Steatosis, HC = , Hepatocellular Carcinoma, M = Hemangioma, T = Total

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