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An information fusion based method for liver classification using texture analysis of ultrasound images

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ABSTRACT

This paper presents a method for classification of liver ultrasound images based on texture analysis. The proposed method uses a set of seven texture features having high discriminative power which can be used by radiologists to classify the liver. Feature extraction is carried out using the following texture models: Spatial Gray Level Co-occurrence Matrix, Gray Level Difference Statistics, First order Statistics, Fourier Power Spectrum, Statistical Feature Matrix, Law's Texture Energy Measures and Fractal Features. Based upon the results of Linear Discriminative Analysis (LDA) followed by box-plot analysis and Pearson's correlation coefficient, 7 best features from a set of 35 features are selected. These selected features are then fused using a linear classifier. The novelty of the proposed method is that, it combines the best features from different texture domains along with their weights and 'weighted z-score' values. Subsequently, these values are used to compute a *discriminative index* for liver classification. The results show that this method has overall classification accuracy of 95% and low computational complexity.

1. Introduction

In medical imaging, fusion of two different imaging modalities is used to get more meaningful information. A recent survey on the use of fusion of different domains of information and their application in medical imaging can be found in the recent publication by Dasarathy [1]. Although, many new modalities like Electrical Impedance Tomography (EIT), Single Photon Emission Computed Tomography (SPECT) and functional Magnetic Resonance Imaging (fMRI) are being used, but ultrasound is still a popular imaging modality because it is able to visualize most of the human tissues without harming them. Some of the well-accepted applications of ultrasound imaging are to monitor the growth of foetus and to diagnose problems of abdomen, kidneys, and liver. In the case of liver, ultrasound is mainly used for the diagnosis of fatty liver (Steatosis). Fatty liver is a condition, that occurs when the fat content of the '*hepatocytes*' increases, resulting in the variation of the texture of liver surface. Therefore, texture analysis may give crucial information which is otherwise difficult to extract by visual examination of ultrasound images. In Indian population, the prevalence of fatty liver condition has been found to be as high as 24% [2]. Visual criteria for detecting diffused liver diseases are generally subjective and it depends on the capability of the radiologist to examine the variation in textural characteristics in the image, and then comparing them with pathological findings. Some examples of these textural features are homogeneity and '*echogenicity*'. However, the description of '*echogenicity*' by visual examination of ultrasound images has been widely debated among experienced radiologists, especially in marginal cases. Diagnostic accuracy through visual interpretation is approximately 72% [3]. The limited accuracy of visual interpretation further augments the need to use an objective method based on quantitative texture analysis for the liver characterization.

To classify the liver (normal and abnormal) tissue in an ultrasonic image, many features have been proposed in the last few years [3,4]. However, the Spatial Gray-Level Co-occurrence Matrices (SGLCM) proposed by Haralick et al. [5], the Fourier Power Spectrum (FPS) by Lendaris and Stanley [6], and the Texture Energy Measures (TEM) suggested by Laws [7] are the most commonly used texture features that have been applied successfully to real-world textures also. The Statistical Feature Matrix (SFM) texture model is also useful to describe surface textures [8]. Gray Level Difference Statistics (GLDS) is proposed by Weszka and Dyer for terrain classification based on texture analysis [9]. The fractal-based features proposed by Mandelbrot are able to explain the roughness of natural surfaces [10]. Wu and others used all the above four texture models for liver characterization, and proposed a new concept based on the multi-resolution fractal dimensions also called Fractal Features (FF) [11]. Thijssen and his team proved the significance of

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SGLCM parameters in characterizing the echo-graphic images [12]. Kadah et al. explored various classification methods to characterize diffused liver diseases [13]. Badavi et al. reported liver classification using texture analysis through fuzzy logic [14], while Mukherji et al. reported a neural-network based classifier [15], and Riberio and Sanches reported a Bayesian classifier [16]. Fractal analysis was explored with the '*k*-mean' clustering for liver by Balasubramanian et al. [17]. Lee et al. used ANN on fractal geometry for liver classification [18]. An SVM based classification method for fatty liver and normal liver was proposed by Li and his team [19]. Recently, 'grey relational analysis' has been proposed to grade the fatty liver [20]. Most of the above-said classification methods are computationally complex. Further, none of the researchers have studied the features collectively to select the optimal ones. Therefore, in this work, an attempt has been made to present a new classification method using fusion of the best features from different domains. To achieve this goal, information related to the surface of liver has been extracted using different texture models like structural, statistical, frequency and fractal. Subsequently, the best features have been selected to combine in such a way that it gives a single quantitative metric to classify the liver.

2. Materials and Methodology

2.1. Image acquisition

The sample images used for analysis were acquired with Voluscan730 PRO (General Electric Medicare) ultrasound machine with 68 mm curved array probe at 3.6 MHz frequency. The Time Gain Compensation (TGC) setting was done in such a way that the background gray level was almost the same throughout the depth. To avoid the effects of liver glycogen and water storage on ultrasound, the patients were told to have 8 h fast before the scan [21]. The present study is conducted on 180 ultrasound liver images (one image per patient), out of which 100 images are used for training (40 normal and 60 fatty liver images) and the remaining 80 images (40 normal and 40 fatty liver images) are used for testing. To avoid any distorting effect, the Region of Interest (ROI) is selected every time along the center of the image. Depth of the ROI is selected in such a way that blood vessels are avoided in ROI. Therefore, the ROI is selected by the experienced radiologists. A 30×30 square sized ROI (900 pixels) is selected from the image to provide a suitable sample size for reliable statistics.

2.2. Methodology

The purpose of the current study is to propose a computer aided method for liver classification, which must be fast and accurate. To increase the rate of correct classification, fusion of different texture models have been used. The basic methodology of the proposed system is represented in Fig. 1.

2.2.1. Texture features extraction

In this study, seven different types of well-known texture models are used to extract features from each ROI. The seven texture models used in this study are SGLCM, GLDS, FoS, TEM, SFM, FPS and FF. The texture features used in these models are given in Table 1. The importance of these texture features in liver surface characterization has been recently established by Singh et al. [22]. All 35 texture features are extracted from training set ultrasound images, whose pathological results are already known and radiologists have also labeled them.

2.2.2. Outlier removal

In the second step, outlier values are removed from the feature data set. Outliers are the isolated values which lie beyond 1.5 times the inter quartile range (Whisker box plot). Whisker box plots have been used for all features to identify the outliers in the feature dataset. Fig. 2 represents the Whisker Box plots for features, *difference of entropy* (DENT), *contrast* (CNT), *ASM* and *H1*. The '+' symbols shown in this figure, are the outlier values and are removed.

2.2.3. Feature reduction

To select the best features, linear discriminative analysis and Pearson's Correlation Coefficient (PCC) are used. In the first step, the highly discriminative features are selected using Fisher's Discrimination Ratio (FDR) [23]. The high value of FDR means that the feature has more power to discriminate between two classes. FDR values and acronyms of all the features are presented in Table 2.

2.2.3.1. FDR. For linear discriminative analysis, FDR of '*n*'th feature can be computed as:

$$FDR_n = \left| \frac{(\mu_{an} - \mu_{bn})}{\sqrt{(\sigma_{an}^2 + \sigma_{bn}^2)}} \right| \quad \forall n \in [1, 35] \tag{1}$$

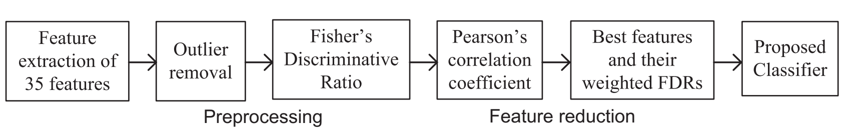

Fig. 1. The block diagram of methodology.

Table 1
List of features from various texture models.

Models	Texture Features						
SGLCM [5]	ASM	Contrast	Correlation	Variance	IDM	Entropy	
	Sum_Variance	Sum_Average	Sum_Entropy	Diff_Variance	Diff_Entropy	Info_meas_1	Info_meas_2
GLDS [9]	Homogeneity	Contrast	Mean	Energy	Entropy		
FoS	Mean	Skewness	Kurtosis				
TEM [7]	LL	EE	SS	LE	ES	LS	
SFM [8]	Periodicity	Roughness	Coarseness	Contrast			
FPS [6]	Radial sum	Angular sum					
FF [11]	Hurst coff. $H1$	Hurst coff. $H2$					