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An integrated index for identification of fatty liver disease using radon transform and discrete cosine transform features in ultrasound images

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ABSTRACT

Alcoholic and non-alcoholic fatty liver disease is one of the leading causes of chronic liver diseases and mortality in Western countries and Asia. Ultrasound image assessment is most commonly and widely used to identify the Non-Alcoholic Fatty Liver Disease (NAFLD). It is one of the faster and safer non-invasive methods of NAFLD diagnosis available in imaging modalities. The diagnosis of NAFLD using biopsies is expensive, invasive, and causes anxiety to the patients. The advent of advanced image processing and data mining techniques have helped to develop faster, efficient, objective, and accurate decision support system for fatty liver disease using ultrasound images. This paper proposes a novel feature extraction models based on Radon Transform (RT) and Discrete Cosine Transform (DCT). First, Radon Transform (RT) is performed on the ultrasound images for every 1 degree to capture the low frequency details. Then 2D-DCT is applied on the Radon transformed image to obtain the frequency features (DCT coefficients). Further the 2D-DCT frequency coefficients (features) obtained are converted to 1D coefficients vector in zigzag fashion. This 1D array of DCT coefficients are subjected to Locality Sensitive Discriminant Analysis (LSDA) to reduce the number of features. Then these features are ranked using minimum Redundancy and Maximum Relevance (mRMR) ranking method. Finally, highly ranked minimum numbers of features are fused using Decision Tree (DT), k-Nearest Neighbour (k-NN), Probabilistic Neural Network (PNN), Support Vector Machine (SVM), Fuzzy Sugeno (FS) and AdaBoost classifiers to get the highest classification performance. In this work, we have obtained an average accuracy, sensitivity and specificity of 100% in the detection of NAFLD using FS classifier. Also, we have devised an integrated index named as Fatty Liver Disease Index (FLDI) by fusing two significant LSDA components to distinguish normal and FLD class with single number.

1. Introduction

Fatty Liver Disease (FLD) or hepatic steatosis is the excessive accumulation of lipids (triglycerides) in the hepatocytes (liver). It is named as Non-Alcoholic FLD (NAFLD) in the absence of excessive alcohol consumption [1] and is the leading chronic liver disease worldwide. Diabetes and obesity are the major risk factors of NAFLD [28]. The estimated prevalence of NAFLD in adult population is around 15–30%, which increases with age [2–4]. It is estimated that the prevalence of NAFLD is 32% of general population in India [5] and 15% in China [6]. Prevalence of NAFLD in diabetics is 74% in North America and 70% in Italy [7,8] due to obesity in Asia ranging from 50% to 80% in Japan, 70–80% in China, 10–50% in Korea [9–13].

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NAFLD pathology may be accompanied with swelling of liver or may advance to an extreme situation, liver cirrhosis, leading to permanent liver damage [14,15]. Nevertheless, the condition may be reversible if diagnosed in its early stage [15,16]. It may lead to fibrosis [17], cirrhosis [18], liver cancer [19,20], liver failure requiring liver transplant [21], and mortality [22]. The pathological changes introduced by this disease can be evaluated using B-mode ultrasound images [23,24]. However, it is associated with the shortcomings such as inter-operator variability, subjective evaluation, and restricted potential to measure the amount of fatty infiltration. Few qualitative reviews [25,26] have challenged the ability of ultrasound to accurately detect fatty liver.

Various computer-aided techniques are proposed for automatic detection of FLD using ultrasound images [27]. Yasser et al., (1996) [28] used gray level features, attenuation and back scattering features for the detection of FLD and reported a sensitivity of 100% using 9 features. Pavlopoulos et al., (2000) [29] used texture features namely Fractal Dimension (FD), Spatial Gray-Level Dependence Matrices (SGLDM), Gray-Level Run Length Statistics (GLRLS), Gray-Level Difference Statistics (GLDS) and First-Order Gray Level Parameters (FOGLP) to discriminate normal and FLD classes. Their method obtained an accuracy of 82.67% using 12 features. Yeh et al. (2004) [16] proposed automated diagnosis of FLD using Gray-Level Co-occurrence Matrix (GLCM) and Non-Separable Wavelet Transform (NSWT). Their method used 10 features and obtained an accuracy of 90.5%.

Lupsor et al., (2011) [30] compared two computer-aided techniques namely, the attenuation coefficient and first order texture features for the FLD (steatosis) assessment using US images. Andreia et al., (2012) [31] used GLCM, Gray Level Run Length Matrix (GLRLM), FD and Law Texture Energy (LTE) to extract the total of 325 features from ultrasound images. Three classifiers namely Artificial Neural Network (ANN), Support Vector Machine (SVM) and k-Nearest Neighbour (k-NN) are used for the classification of liver steatosis (FLD). Their study showed that the SVM classifier achieved an accuracy of 79.77% compared to other classifiers tested.

Ricardo et al., (2009, 2012) [32,33] proposed Computer Aided Diagnosis (CAD) system for steatosis analysis and classification using texture feature extraction method. The texture features (attenuation coefficient and Auto Regressive (AR)) are extracted using Discrete Wavelet Transform (DWT) detail coefficients of ultrasound images. The Bayes classifier achieved an overall accuracy of 93.54% and 95% for the classification of normal and steatosis classification using AR coefficients features extracted from the multi-scale Haar wavelet decomposed ultrasound images. Singh et al., (2012, 2014) [34,35] developed a new quantitative method for liver classification (normal and FLD) using ultrasound images. Their study used five different texture feature extraction methods (i) spatial gray-level dependence matrices, (ii) statistical feature matrix, (iii) LTE, (iv) Fourier Power Spectrum (FPS) and (v) fractal features from the ultrasound images. The study used statistical and linear discrimination analysis to select the best features and achieved an accuracy of 92% and 95% using 6 and 7 texture features respectively.

Acharya et al., 2012a [36] presented a CAD technique (called Symtosis) for the automated detection of FLD using texture, DWT, and Higher Order Spectra (HOS) bispectrum features extracted from ultrasound images. They have reported an average accuracy of 93.3% using decision tree classifier. Minhas et al., (2012) [37] presented a novel approach for detection of FLD using texture analysis of liver ultrasound images. Their study used multiscale analysis capability of Wavelet Packet Transform (WPT) to extract statistical features which changes in echogenicity, granularity and homogeneity of ultrasound due to the incidence of FLD. Their method claimed classification accuracy of 95% using leaner SVM classifier. Recently, Dan et al., (2013) [38] discussed and compared the CAD method for steatosis rating (severity) in ultrasound images using Radon Forest (RF) and SVM classifiers.

RT-DCT based approach is used for face recognition [39]. However, the available literatures show that there is no study used RT-DCT based approach for automated fatty liver disease detection. Moreover, RT-DCT combination captures the subtle changes in the images [39]. Hence, this paper proposes a novel approach for an automated detection and classification of ultrasound FLD using Radon Transform (RT), Discrete Cosine Transform (DCT), and Locality Sensitive Discriminant Analysis (LSDA) method [39]. In this method, the ultrasound images of normal and FLD are preprocessed to enhance the image contrast and subjected RT for every 1° angle to obtain the Radon projections from 0–179°. DCT is performed on those Radon projections to obtain the DCT coefficients matrix. DCT coefficients matrix which is the frequency coefficients are arranged in zigzag manner to obtain a vector features arranged in the increasing frequency arrangement. Hence, these DCT coefficients are converted to 1D array of coefficients. All the 1D DCT features are subjected to LSDA data reduction method to reduce the number of features to 30. These reduced numbers of features are ranked using minimum Redundancy and Maximum Relevance (mRMR) ranking method. Highly ranked features are fed to Decision Tree (DT), k-NN, Probabilistic Neural Network (PNN), SVM, Fuzzy Sugeno (FS) and AdaBoost classifiers one by one to get the highest classification performance using optimum features. Detailed descriptions of each step are explained in the following sections.

2. Data used

One hundred ultrasound liver images were used to evaluate the performance of our methodology. Fig. 1 shows the normal and FLD ultrasound images. Among these 100 cases, 50 were abnormal (affected by FLD) and 50 were normal images. The ultrasound images of normal and fatty livers were acquired by expert operators with the ultrasound equipment in University of Malaya Hospital, Malaysia. All the images were collected from routine cases and were consecutively recruited. The ethical clearance was obtained from the ethical review committee of University of Malaya Hospital, Malaysia. The ultrasound images were obtained by a Philips CX© 50 ultrasound machine. All images were captured with 1898 × 888 and 1418 × 720 pixels with a gray level resolution of 8 bits/pixel. Images were stored in the Digital Imaging and Communications in Medicine (DICOM) format. The broadband curved array transducer C5-1 from Philips© was used. It is composed by 160 piezoelectric elements with a curved array shape, and had the operating frequency range from 1 to 5 MHz.

The ultrasound machine is preset for this study, after the calibration step. Ultrasound is calibrated at 3.5 MHz frequency, an image depth of 15 cm. The dynamic range was set to 70 dB with variable gain. Time gain compensation (TGC) maintained constant by setting it to its central position throughout the procedures, eliminating this variable parameter. The ground truth of each image whether normal or abnormal was determined manually by the operators and confirmed by laboratory analysis.

3. Methodology

This paper used a new method of automated detection of NAFLD in which DCT frequency features are extracted from the RT of the images. The block diagram of an automated FLD detection system is shown in Fig. 2. The current method comprises of four stages: (i) in the first stage, the ultrasound images are preprocessed, (ii) in the second stage, the RT is performed for every 1° angle to obtain the RT projections of an image, (iii) in the third stage, the DCT is used on the whole RT projections to acquire the