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Automated stratification of liver disease in ultrasound: An online accurate feature classification paradigm

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ABSTRACT

Purpose: Fatty liver disease (FLD) is one of the most common diseases in liver. Early detection can improve the prognosis considerably. Using ultrasound for FLD detection is highly desirable due to its non-radiation nature, low cost and easy use. However, the results can be slow and ambiguous due to manual detection. The lack of computer trained systems leads to low image quality and inefficient disease classification. Thus, the current study proposes novel, accurate and reliable detection system for the FLD using computer-based training system.
Materials and methods: One hundred twenty-four ultrasound sample images were selected retrospectively from a database of 62 patients consisting of normal and cancerous. The proposed training system was generated offline parameters using training liver image database. The classifier applied transformation parameters to an online system in order to facilitate real-time detection during the ultrasound scan. The system utilized six sets of features (a total of 128 features), namely Haralick, basic geometric, Fourier transform, discrete cosine transform, Gupta transform and Gabor transform. These features were extracted for both offline training and online testing. Levenberg–Marquardt back propagation network (BPN) classifier was used to classify the liver disease into normal and abnormal categories.
Results: Random partitioning approach was adapted to evaluate the classifier performance and compute its accuracy. Utilizing all the six sets of 128 features, the computer aided diagnosis (CAD) system achieved classification accuracy of 97.58%. Furthermore, the four performance metrics consisting of sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) realized 98.08%, 97.22%, 96.23%, and 98.59%, respectively.

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Conclusion: The proposed system was successfully able to detect and classify the FLD. Furthermore, the proposed system was benchmarked against previous methods. The comparison established an advanced set of features in the Levenberg–Marquardt back propagation network reports a significant improvement compared to the existing techniques.

1. Introduction

Fatty liver disease (FLD) is a liver condition where fat gets deposited in the liver cells through a process called steatosis. Both alcoholic and non-alcoholic FLD may lead to critical liver diseases such as cirrhosis, liver cancer, and inflammation [1,2]. Early detection of the FLD is of great significance to save the patient's life as well as to reduce the cost associated with providing treatment against advanced liver diseases. Liver biopsy is the standardized method for detecting steatosis. It is an invasive technique that causes discomfort while being prone to sampling errors [3–5].

There are several noninvasive techniques such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). These techniques had been successful in detecting fat deposit in liver but they are inefficient in detecting steatosis by less than 25–30% [6,7]. Ultrasound techniques have a sensitivity of around 82–94% and specificity more than 82% for fatty liver detection [8–11]. Although ultrasound is more sensitive than CT [12], it turns out to be less specific and has a poor visualization for obese patients.

In the case of CT imaging, fatty liver creates a lower attenuation for the hepatic parenchyma compared to the neighboring blood vessels, spleen, and kidney. The contrast in attenuation assists in the detection of steatotic liver. CT imaging technique requires different calibrations for different types of scanners; additionally it requires patient pre-qualification diagnosis due to ionizing radiation. On the other hand, MRI provides anatomical information of the imaged liver [13]. MRI can detect small amounts of fat of less than 33% presented in the liver [14]. MRI techniques are relatively more complex to implement for liver imaging, while being expensive and time consuming. In order to get good MRI of the liver, good spatial resolution, high SNR value and adequate compensation for nullifying the patient motion are essential.

Among all the techniques discussed above, ultrasound is the most commonly used technique due to its worldwide availability in clinical practice. In order to improve the specificity of the ultrasound and to correct the inter-observer issues, machine learning techniques have been developed to accurately classify the FLD in ultrasound liver images. These techniques utilize the acquired ultrasound images to extract meaningful and distinctive features that are capable of distinguishing a normal liver from a cancerous liver. These features are then provided as input to the supervised learning-based classification algorithms in order to stratify different tissue types of liver.

FLD targets the liver which in turn changes the texture of the liver ultrasound images. Fat deposition occurs in the liver which gives rise to increased brightness in the ultrasound and causes changes in image texture. Hence, texture of the liver's image has been one of the key distinctive features that are used in this work.

The main contribution of the current work is to study a wide set of features to train an automated CAD system using back propagation network. In addition, the current report studies the effect of different types of back propagation networks. Amongst which the Levenberg–Marquardt back propagation network reported a significant overall improvement of FLD classification accuracy compared to the current state-of-the-art methods. Moreover, this study compares the involvement of different feature sets to find out a wide variety of feature sets used to achieve accuracy of 97.58% as well as to study the classification capability of a subset of features.

The structure of the remaining sections is as follows. Section 2 includes the literature review on the liver classification, followed by the materials and the proposed system in Section 3. The methodology for feature extraction and classification methods is presented in Section 4. The implementation of Levenberg–Marquardt back propagation Neural Network is demonstrated in Section 5. The results and discussion are presented in Sections 6 and 7, respectively. Finally, the proposed study concludes in Section 8.

2. Literature review

Various automatic classifications for the liver ultrasound images have been addressed as follows. Kyriacou et al. [15] utilized five set of features namely: first order gray level parameters (FOP), fractal dimension texture analysis (FDTA), the gray level difference statistics (GLDS), the spatial gray level dependence matrices (SGLDM) and the gray level run length statistics (RUNL). The image's data consisted of 30 samples each corresponding to three different sets of ultrasound types, namely fatty, cirrhosis and normal. The region of interest (ROI) of 32×32 pixels in size was delineated by an expert physician before any feature extraction. Using the summation of FDTA along with SGLDM features, the K-nearest neighbor (KNN) classifier gave an accuracy of 82.20%. In a different research study conducted by the same group [16], the algorithms on four sets of images, namely: fatty, cirrhosis, hepatoma and normal were applied. The study achieved an accuracy of 80% after combining the feature set SGLDM, RUNL and FDTA in KNN-based classifier. Based on geometrical fuzzy sets, a novel neural network classifier was employed by Kyriacou et al. [17], which achieved an accuracy of 82.67% in identifying normal, fatty, and cirrhotic liver images.

Wan and Zhou [18] analyzed the features extracted through using wavelet packet transform (WPT) for B-mode ultrasound liver images. There are nearly thirty two features obtained from 200 cirrhosis and 390 normal samples which were