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Review Article

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Computer-Aided Diagnosis Approaches to Fatty Liver Disease According to Sonographic Images Based on Wavelet Transform: A Review Study

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Abstract

Introduction: *Fatty liver is usually diagnosed by ultrasound, but this diagnosis can be difficult because the disease does not always lead to abnormal conditions on gray levels that can be detected by the eye. However, ultrasound is still the first choice to detect fatty liver due to its low cost and availability, and the lack of side effects. The study reviewed Computer-Aided Diagnosis approaches to fatty liver disease, based on wavelet transform sonographic image processing.*

Methods: *In this review study, a search was conducted based on related keywords and articles that had been published in English over the last 12 years. The findings were extracted based on the aim of study.*

Findings: *Nowadays wavelet transformation has been widely used in the field of medical image processing because of its adaptability to the characteristics of the human eye system. The well-known wavelets used to liver diseases detection include Haar, Symlet, Daubechies and Gabor. Extracting the proper properties of images plays an important role in detecting diseases. Important statistical features of image textures are: statistical descriptors based on the intensity histogram and the GLCM matrix (Gray level Co-occurrence Matrix). The popular algorithms used for liver disease include neural network, Support Vector Machine (SVM), Bayesian, decision tree, K-Nearest Neighbor (KNN), and regression.*

Conclusion: *The sensitivity, specificity and accuracy of the extracted statistical features of the output components of wavelet transform are generally better than those obtained from the original image itself. Gabor's wavelet transformation often has a higher efficiency than the Daubechies and Symlet wavelet transforms because the two transforms only break up the half-band of low frequencies and lose some of the intermediate frequency regions, while Gabor retains all of the frequency regions This precision also mainly depends on the type of features selected and the type of classification. Statistical features based on intensity histograms do not provide relative information about the spatial of pixels relative to each other. To enter this spatial information of pixels in a texture analysis, it is recommended to use GLCM matrix in gray images. The type of classifier used can significantly impact on the precision of the final diagnosis.*

Keywords: Fatty Liver, Sonographic Images, Computer Aided Diagnosis, Wavelet Transform, Glcm Matrix.

Introduction

The most important diseases of the liver are fatty liver, hepatitis and cirrhosis [1-3]. Fatty liver disease is the accumulation of fat if it is more than 5% liver weight, is asymptomatic, and the level of aminotransferase serum is gradually increased while the possibility of other chronic liver diseases is rejected [4,5]. In Simple steatosis, there is no inflammation and fibrosis (stiffness), but, inflammation, fibrosis, and damage to liver cells is seen in Steato Hepatitis. In case simple Steatosis leads to Steato Hepatitis, it increases the risk of cirrhosis or Hepato Cellular Carcinoma [6,7]. The prevalence of fatty liver in the general population of the Middle East is about 20 to 30% [8]. Knowing that fatty liver can be recovered in early stages, the early diagnosis is of particular importance [9]. In general, the current approaches for the diagnosis of diffused liver disease are divided into four groups: pathology (liver biopsy), laboratory, anthropometric and imaging [6,10-12].

Liver biopsy

This approach is known as a gold standard for diagnosis of liver disease, but this method is invasive, and only one fifty thousand parenchyma of the liver is evaluated, and its sampling error is high [4, 13].

Laboratory methods

Liver enzymes enter the patient's serum with hepatocellular destruction, and their increase indicates the liver cell destruction [6, 11]. Enzyme disorders in the liver are usually mild. Basically, there is no specific test to distinguish simple Steatosis from fatty liver hepatic, and in some cases, differential detection of fatty liver disease from other liver diseases is difficult with laboratory methods [4, 6, 10].

Demographic and anthropometric approach

This approach is most often used for fatty liver and rarely used for hepatitis and cirrhosis. For example, Body Mass Index (BMI) can be a good property for fatty liver detection. However, similar to laboratory approaches, these approaches don not have adequate sensitivity and specificity [12].

Imaging methods

Imaging approaches such as sonography, CT scan and MRI can provide important information on structural changes in the liver. Sonography is the most commonly used imaging diagnostic approach for fatty liver due to low cost, convenience of performing, and acceptance by patients [5]. Typically, fatty liver is diagnosed through sonography images with an eye evaluation to increase the intensity of its texture. The image of the liver is soft and its echogenicity is obtained in comparison with the renal cortex or spleen [3]. However, this approach is subjective rather than being quantitative and objective. The diagnosis of diffuse liver diseases based on sonographic images can be difficult by physicians, because these diseases do not always cause abnormalities in gray levels and are often non-specific [2]. Therefore, physicians need a computerized decision-making system to quantify and evaluate the texture of liver based on sonographic images and independent of the type of ultrasound device. These problems can be eliminated using image processing techniques [14,15].

The wavelet transforms techniques, feature extraction and classifications in image processing are used in computer-aided diagnostic approaches. In wavelet transform, images are divided to parts, and then the appropriate features of the transformed image are extracted. Using this approach, fatty liver can be diagnosed efficiently with appropriate methods of classifying. The wavelet transform has been widely applied to image processing due to its adaptability to the characteristics of the human eye system. One of the important features of the texture of an image can be referred to statistical descriptors based on the intensity histogram and the GLCM matrix. Classification has different types that the right choice can have a significant impact on the accuracy of the computer-aided diagnostic system.

The aim of this study was to review computer-aided diagnosis approaches to fatty liver disease, through sonographic image processing based on the wavelet transform with the aim of finding extractable and appropriate features of images, and choosing the appropriate classifier for this purpose.

Methods

To find related articles, a combination of sonography images, diffuse liver disease, fatty liver, computer-aided detection, wavelet transform, feature extraction, and classification were used. The relevant English language studies undertaken in last 12 years were selected for review. Extracting the findings from articles was performed based on key aspects such as wavelet types, feature extraction, and the method of classification.

Background

The algorithms for the detection and classification of diffused liver disease with image processing techniques generally consist of the following five main stages: selection of the target region, improvement of image quality, transformation of selected images to new spaces including wavelet transform, feature extraction, and classification [16,17].

The purpose of selecting the target region is to separate the proper portion of the liver from the entire ultrasound image, and this selection can be done automatically, semi-automatically, or manually.

Enhancing the quality of the image could be addressed in two spatial and frequency domains. In the spatial domain, image pixels are directly manipulated. In the frequency domain, the Fourier transform or wavelet transform of the image are changed. A common problem in ultrasound images is the speckle noise generated from heterogeneous tissues. Speckle noise is an inherent phenomenon in the majority of coherent imaging systems, such as laser and ultrasound imaging, and is experienced due to a random interference between echoes of signals. This noise reduces the quality of the details and edges of the image and usually appears as a granular pattern in the image [18-20].

Wavelet transform

WT is based on the sub-band encoding method, which provides multi-resolution analysis. In sub-band encoding, an image is decomposed into a set of finite-bandwidth components, called sub-bands. In this type of decomposition, the sub-bands can be recombined to reconstruct the original image with no error. The wavelet transform method for decomposing and rebuilding images uses the digital filter technique and divides the image into four components. A two-dimensional image, first in a row, and then in a column, passes through the low pass and high pass filters. The low pass filter output is the average of signal, and the high pass filter output shows the details of signal. The low pass filter output indicates the overall shape of the signal, and for this reason it is called approximation. The high pass filter output contains the signal details that include vertical, horizontal and diagonal components.

Therefore, the wavelet transform divides the image into four bands (images) called wavelet decomposition process. In order to construct the initial image, it is necessary to use the inverse wavelet transform, used as a composite section. The initial signal is reconstructed through inverse LPF and inverse HPF. The parsing steps can be repeated in multiple levels. In other words, the approximation can be again divided into four smaller components. Wavelet transformation applications in image processing include noise reduction, segmentation, image enhancement, edge detection, image encoding and compression. There are different types of wavelet transform, including Haar, Symlet, Daubechies, and Gabor [17,21-23]. In a study WPT (Wavelet Packet Transform) was used to detect fatty liver from the normal liver, providing a multi-resolution analysis at all frequencies. The extracted features from coefficients of this wavelet were median, standard deviation and IQR, and the sensitivity of the proposed algorithm with the SVM classifier was announced 78.8% for detecting fatty liver and 90.2% for normal liver [8]. In another study, to detect normal liver from fatty liver, Haar wavelet and Bayesian Classifier was used, and accuracy 95%, sensitivity 100%, and specificity 95% were reported [24]. In a research to differentiate 2, 8, or 10 different textures, a Daubechies wavelet was used, and for two textures in one image, 0.5% error was reported, for 8 textures in one image 11% error, and for 10 textures in one image 18% error was obtained [25]. In another study, Gabor wavelet was used to detect liver cirrhosis.

The proposed model had a total accuracy 98% [26]. In a study, four methods were used to diagnose normal liver, hepatitis and cirrhosis. These methods included statistical, Daubechies wavelet, Symlet wavelet and Gabor wavelet. In the statistical technique, the mean value, variance and smoothness of the image were extracted, and for the wavelets, the mean and energy of each component were extracted and then the classifier of minimum distance was used. With Gabor wavelet, the sensitivity and specificity of cirrhosis diagnosis were announced 86% and 79% respectively, and the same criteria for detecting hepatitis reported 85% and 77%, respectively. With the Symlet and Daubechies wavelet, the same criteria for cirrhosis was 78% and 72%, and for hepatitis 77% and 65% respectively. The result of Gabor wavelet proved to have better results [27].

Feature extraction

The three main methods for describing the texture of a region are statistical, structural and spectral methods. In most studies, statistical methods have been used to process liver images. Statistical methods are based on the distribution of gray levels of the image. In structural methods, texture is described based on a series of basic shapes. Knowing that the liver image lacks these basic forms, the structural methods are not used for this purpose. Spectral methods operate on the basis of the Fourier spectrum, and because they lack the spatial information of the pixels, they cannot accurately analyze the liver texture. Statistical methods are more appropriate for feature extraction of liver texture, because they act similar to the physicians' diagnostic approaches, according to the softness and roughness of the texture [16-18, 21]. The important statistical features of the texture can be statistical descriptor based on the histogram of intensity, and statistical descriptors based on GLCM matrix [9,21,28]. The statistical features based on histogram are mean, standard deviation, relative smoothness, third moment, uniformity and entropy. Mean shows the intensity of the texture. Standard deviation is intensity variation around the mean, or, in other words, the mean texture contrast. Relative smoothness is zero, for areas with constant intensity, and for large values of variance, the smoothness goes to number one. Third moment shows skewness of the histogram. Uuniformity or energy indicates the uniformity of the image texture. Entropy shows the degree of irregularity and randomness of the image.

The GLCM matrix specifies the number of couple's image pixels having the specified intensities, have been placed with a specific distance and direction. By the GLCM, four features of contrast, correlation, energy and homogeneity were extracted and added to the set of statistical features [9,16-18]. Contrast calculates the brightness between a pixel and its adjacent pixels over the entire image. Correlation is a feature in the range that represents the correlation or linearity of a pixel and its adjacent pixels in the entire image. Energy is in the range, and by decreasing the smooth texture, this feature is reduced. Homogeneity is in the range and it is a criterion of uniformity of the image [9,16,17,21]. Often, for the GLCM matrix, angles of 0, 45, 90, and 135 degrees are considered. GLCM matrix can be calculated in four directions of 0, 45, 90 and 135 degrees, and then their average values are considered for the calculation of the features [29-32]. In a study to differentiate normal liver, fatty liver, cirrhosis and Hepatomegaly, the features of intensity histogram, GLCM matrix, and neural network classifier have been used. For intensity histogram, accuracy was 77%, sensitivity 75% and specificity 80%. For GLCM, accuracy was 90%, sensitivity 95%, and specificity 95%, and therefore GLCM matrix has given the better result [9]. In another study, the extracted features of GLCM were used to categorize 4 image types. Using the neural network classifier, accuracy was 97.75% [28]. In another study, the extracted features of GLCM matrix were used to detect malignant and benign breast masses. Using 8 features from GLCM, accuracy 95% and AUC 99% were obtained [33].

Classification

The general algorithms of classification used in categorizing liver diseases include neural network, SVM, Bayesian, KNN, minimum distance, and regression. In a study, SVM with RBF kernel was used to differentiate normal and fatty liver, accuracy 84% was obtained for normal liver and 97% for fatty liver [8]. In a study, the SVM classifiers with a polynomial kernel of grade 2 and KNN with K = 1 were used for the detection of normal and fatty liver; with SVM performance with an overall accuracy 91% better than KNN with a accuracy 82% [15]. Another study was performed to differentiate the normal and fatty liver by Bayesian classifier, and the accuracy 95%, the sensitivity 100% and the specificity 95% was obtained [24]. In a study, a minimum distance classifier was used to differentiate between normal liver, hepatitis and cirrhosis, and the sensitivity and specificity of cirrhosis was 86% and 79%, respectively for hepatitis 85% and 77% [27]. In another study to distinguish normal from fatty liver, simple features such as median, tenth and ninetieth percent normalized intensity and the skewness were extracted from the original image, and then the SVM classifier was used with different kernels. The SVM with the RBF kernel showed 85% precision, sensitivity 96%, and a low specificity 25% [14]. Another study used the neural network classifier to distinguish between normal liver, fatty liver, hepatomegaly and cirrhosis, reporting the accuracy, sensitivity and specificity 95% [9].

Findings and discussion

The results of reviewing the computer aided approaches for detecting fatty liver based on sonographic images are presented as follows:

- Selection of the area: There are several standard methods for automatic or semi-automatic segmentation of abdominal ultrasound images, including threshold, edge detection (such as Canny edge detector and Hough transform), area growth, texture analysis, and watershed method [17, 18, 34, 35]. In each image, several areas of the liver may be selected, and these areas should be homogeneous and should not include blood vessels, bile ducts and shady areas. Research indicates that the manual method of texture cutting has more popularity than the computer-based approach due to simplicity and speed of cutting in the former method, and the point that automated or semi-automated methods are not error-free [14,15,27].

- Improving image quality: The main goal in improving the quality of ultrasound images is to eliminate the speckle noise from images with minimal missing of edges and the main features of the image. This noise occurs specially in images of soft organs such as the liver and kidneys [36; 37; 38]. Some methods used to eliminate the speckle noise include adaptive mean filter and diffusion filters. The approximation component of the wavelet transform is another suitable method for noise elimination [19,20,37,38].
- Wavelet transform: Fourier transform of a signal only determines which frequencies are included in the initial signal, but does not indicate their occurrence time. Therefore, some pieces of the information in the time domain are lost, while the wavelet transform causes the synchronization information of the time and frequency of the signal to be available [17]. The advantage of this method is the maximization of the energy in both spatial and frequency domains [27]. The simplest wavelet transform used to diagnose liver disease is Haar wavelet. Other wavelets used in this field are Symlet, Daubechies and Gabor. The Symlet and Daubechies wavelets extract the image details in horizontal, vertical, and diagonal directions, and the Gabor wavelet allows finding details at multiple angles [17,22,23]. The Gabor wavelet is often more efficient than the Symlet and Daubechies wavelet because these two wavelet transform methods analyze only half band of low frequencies and lose part of the intermediate frequency regions. However, the Gabor method addresses all frequency regions and the most basic texture information is focused mainly on regions with intermediate frequency. On the other hand, in the transform of Symlet and Daubechies wavelet, the spatial frequency page is analyzed only logarithmically, while in the Gabor method, the frequency bands are decomposed using a combination of two logarithmic and linear methods. Therefore, Gabor is a more flexible method in terms of the decomposition of the entire frequency band which generally leads to high capability in the separation of texture information [27].
- Extraction of features: the statistical descriptors of texture based on intensity histograms do not provide information about the location of pixels relative to each other, while the information about the location of pixels is important to diagnose disease [9, 16, 21, 28]. Therefore, the histogram method is used to differentiate between two diseases whose intensity histogram is completely different. However, for diffuse liver diseases where the location of this intensity is important, the spatial information of the pixels should be provided using GLCM matrix. This approach could help to simplify the differential diagnosis of diseases that have relatively similar ultrasound images [9,21,28].
- Classification: The final result of classifiers outputs is greatly dependent on the type of classifier. In other words, for each application, a particular classification may be more appropriate. The classifiers have several setting options affecting the accuracy of the result. Therefore, the selection and use of only one classifier at the beginning of a study may not give the best precision for the diagnosis of disease. For this reason, it is necessary to use comparative methods involving several classifiers for a better result.

Conclusion
Due to the use of different modalities, the relatively low quality of sonographic images and physical differences in patients, detection of diffuse liver diseases is often qualitative and depends on physician's judgment. The use of Computer Aided Diagnosis systems (CADs) makes detection of the disease faster, more accurate and independent of the judgment of the physician. Sensitivity, specificity and accuracy of the statistical features extracted from the output components of the wavelet transform are better than the features obtained from the original image itself. The wavelet transform has several types, each of which has several parameters. A particular type of wavelet with specific settings could respond better for each application. In most of the reviewed studies, standard wavelets of Haar, Daubechies, Symlet and Gabor had been used. In addition, the efficiency of these CADs depends on the type of features extracted and the type of classifier. In order to extract the effective features of images from the existing set of properties, it is preferable to act based on statistical descriptors of intensity histograms as well as methods that include the information of location of pixels relative to each other. Finally, the type of classifier could influence the precision of the final diagnosis.

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