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Detection of pathologic liver using ultrasound images

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ABSTRACT

Fatty liver or steatosis is a pathology characterized by fat accumulation in the liver cells. Ultrasound is the most common technique used for its evaluation, however the diagnosis is strongly dependent on the physician's expertise and system settings. These drawbacks have motivated the development of procedures for the quantitative analysis of ultrasound images to help the steatosis diagnosis. In this work, three approaches are presented and tested with human liver images. The first one addresses textural analysis of the hepatic parenchyma using five classifiers, 357 features, a feature selector, and classifiers fusion. Its performance is measured by two parameters: accuracy and area under the ROC curve. The second makes use of the hepatorenal coefficient followed by a statistical analysis to discriminate echogenicity differences between liver and kidney. The third is based on the acoustical attenuation coefficient evaluated over a line traced in the images with parallel orientation to the acoustical beam. The use of classifiers fusion has provided better results (accuracy of 0.79), when compared with the performance of the best one considered alone (0.77 for ANN). The hepatorenal coefficient proved to be a good parameter for steatosis detection with calculated sensitivity and specificity of 0.90 and 0.88, respectively. It was observed the hepatorenal coefficient is not influenced by the ultrasound machine parameters. The attenuation coefficient provided lower sensitivity and specificity values than the ones from the hepatorenal coefficient.

1. Introduction

Technological advances in the last decade have provided the growth of two important concepts: computer vision and image processing. The combination of these two concepts enabled the development of new tools capable to provide additional information. The medical area has benefited from those technological advances. For instance, the diagnosis of liver diseases has been improved by using image processing techniques, greatly contributing for a more effective evaluation of steatosis, which is characterized by fat accumulation in liver. Fatty liver tissue is potentially risky as it might lead to untreatable diseases, namely steatohepatitis, cirrhosis or hepatocellular carcinoma [1]. Biopsy is the most effective technique used to detect those diseases, however it is invasive and uncomfortable for the patients [2,3]. Should detected at an early stage steatosis can be reversed, which strengthens the need for an effective diagnosis and treatment [4,5].

Several computer-aided diagnosis (CAD) systems have been applied for assisting physicians in the early detection and characterization of pathologies in organs as the liver, breast, thyroid and lungs, using ultrasound images [6,7]. The CAD systems may be assisted by segmentation methods to identify not only the hepatic region, but also the heart cavities [8–10], lungs [11–13] and also vascular or neural structures from the eye [14,15].

Ultrasound is the most used technique in steatosis evaluation. However, ultrasound images are susceptible to misinterpretation and some subjectivity, which has justified the development of methods capable of processing the data provided by that technique [16]. Unlike the computed tomography, which uses the Hounsfield units the ultrasound images do not have an absolute quantitative reference as the pixels may not have the same values for images acquired by different equipments (using a higher/lower gain (more/less bright pixels). To overcome this difficulty a

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qualitative analysis is done based on the comparison between the liver echogenicity and the surrounding organs as the kidney, spleen and pancreas [17,18]. In a normal liver the echogenicity is equal to or slightly greater than the echogenicity of the renal cortex and spleen. The main changes in ultrasound images by steatosis are expressed by:

- Higher hepatic parenchymal echogenicity than the renal cortex and spleen due to the greater number of intracellular deposits of fat in the liver;
- Higher attenuation as the ultrasound wave goes deeper, producing poor visualization of the diaphragm and weak intrahepatic delineation;
- Portal and hepatic veins presenting lower details as a result of the compression caused by excess fat [18–21].

The steatosis diagnosis by visual analysis has a strong subjectivity, due to the following difficulties. First, changes in the echogenicity of structures used for comparison (kidney and spleen) can occur, because they are also prone to diseases. Second, intra-observer and inter-observer variability always exists in diagnoses. Third, variations in the ultrasound machine parameters give rise to different levels of echogenicity. Also, the occasional irregular distribution of fat in the liver parenchyma can lead to misinterpretation [18].

This work aims to overcome the subjectivity occurring when analyzing the hepatic regions as well as to assist the physician in the diagnosis task. It is intended to be a medical diagnosis complement working as an important images analysis tool. The proposed methodology is different from traditional methods since it uses a large number of features and several classifiers, including fusion of classifiers, complemented with a features selector to enhance the most important features.

2. Dataset

For the present work a large number of echographic images were collected by expert physicians using an ultrasound machine (GE Logic E9) and a 4 MHz convex probe. The images were acquired with a resolution of 8 bits (256 grayscale levels), then converted to high quality (low compression) JPEG format in order to reduce their size, with 720×960 pixels, and then analyzed by MATLAB. The patients agreed with the use of images for research purposes by a written permission.

A first dataset corresponds to 120 patients, where the images were singly adjusted by changing the overall gain and the time gain compensation (TGC) to achieve the best contrast. Two expert physicians analyzed the images and classified them as normal (68) and steatotic (52) livers.

A second dataset is composed by 42 images (two for each patient), where the parameters overall gain (set to 60) and TGC (set to 10) were kept unchanged. For each patient, an image was collected according to the sagittal plane for the hepatorenal coefficient calculation, and the other one acquired from an intercostal space for the attenuation coefficient evaluation and textural analysis. From this dataset, 22 were classified as having steatosis and the remaining 20 were considered normal.

For the experimental study, large hepatic regions were delineated by physicians. Whether normal and pathological regions exist in the same image they are labeled accordingly. Then, small regions of interest (ROIs) were automatically selected within those large regions. The number of ROIs varies with the size of each one and the size of the selected regions.

3. Methodology

The proposed methodology is based on three approaches. The first one performs the textural pattern analysis from the liver parenchyma. The second, studies the echogenicity differences between the liver and the renal cortex, and the third evaluates the image attenuation (in depth) along the hepatic parenchyma. All methods are singly implemented for the steatosis diagnosis.

3.1. Method 1: textural analysis

For the textural characterization, 648 non-overlapping ROIs (480 used as a first dataset and 168 as a second dataset) were automatically extracted from the hepatic parenchyma, which was previously defined by a physician. The extraction procedure is illustrated in Fig. 1. In this process, regions with hepatic blood vessels, bile ducts, artifacts caused by the presence of bony structures or other regions hypo/hyper-reflective have been avoided. Better results were reached with ROIs of fixed 50×50 pixels, which size was kept throughout the analysis in order to provide reliable outcomes [22].

For features extraction three statistical approaches were considered: first order statistics (FOS), second order statistics, and higher order statistics. Ten features were extracted based on FOS: average, variance, standard deviation, obliquity, kurtosis, median, range, power, entropy and mode [23]. The following descriptors based on the gray level co-occurrence matrix (GLCM), were extracted as second order statistics: energy, entropy, contrast, variance, homogeneity, correlation, mean of the sum, mean of the entropy, variance of the sum, variance of the difference, entropy of the difference; computed for a distance between pixels, $d = 1$, and directions $\theta = 0^\circ$, $\theta = 45^\circ$, $\theta = 90^\circ$, $\theta = 135^\circ$ [24]. Nine GLCM matrices were constructed. As higher order statistics, eleven texture descriptors based on the gray level run length matrix (GLRLM), were also extracted: short run emphasis, long runs emphasis, gray level non-uniformity, run length non-uniformity, run percentage, low gray level run emphasis, high gray level runs emphasis, short run low gray-level emphasis, short run high gray-level emphasis, long run low gray-level emphasis, long run high gray-level emphasis; computed for directions $\theta = 0^\circ$, $\theta = 45^\circ$, $\theta = 90^\circ$, $\theta = 135^\circ$ [25]. Four GLRLM matrices were constructed.

Features including parameters of Gabor filter as frequency, orientation, eccentricity and symmetry, computed for angles ranging from 0° to 175° with step of 25° [26]; textural properties from texture energy measures as the average gray levels, boundaries, points, ripples, and waves [27,28]; and the fractal dimension and the lacunarity [29,30], were also extracted.

The feature values were normalized to avoid predominance of ones relative to others. For each ROI, the extracted feature values were combined in vectors shape forming a 2D matrix, whose lines identify the ROIs and columns correspond to features. An additional column was added to the matrix with the physician's information related to the presence or absence of pathology in terms of "yes" or "no", respectively.

These features were used in the classifiers artificial neural networks (ANN), support vector machine (SVM), k-nearest neighbor (kNN), Naive Bayes (NB) and decision tree (DT) in order to evaluate their performance in classifying the pathology. The algorithms were developed to produce a binary classification only, such as fatty or normal liver.

The data can be partitioned according to the hold out and the cross validation criteria. The hold out consists of a simple separation of data in training and test sets. Typically 70% of the data is used for training and 30% for testing [31]. The cross validation integrates several techniques for resampling, where the k-fold is the most used. The k-fold is suitable for situations where there is a limitation