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Automated diagnosis of focal liver lesions using bidirectional empirical mode decomposition features

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ABSTRACT

Liver is the heaviest internal organ of the human body and performs many vital functions. Prolonged cirrhosis and fatty liver disease may lead to the formation of benign or malignant lesions in this organ, and an early and reliable evaluation of these conditions can improve treatment outcomes. Ultrasound imaging is a safe, non-invasive, and cost-effective way of diagnosing liver lesions. However, this technique has limited performance in determining the nature of the lesions. This study initiates a computer-aided diagnosis (CAD) system to aid radiologists in an objective and more reliable interpretation of ultrasound images of liver lesions. In this work, we have employed radon transform and bi-directional empirical mode decomposition (BEMD) to extract features from the focal liver lesions. After which, the extracted features were subjected to particle swarm optimization (PSO) technique for the selection of a set of optimized features for classification. Our automated CAD system can differentiate normal, malignant, and benign liver lesions using machine learning algorithms. It was trained using 78 normal, 26 benign and 36 malignant focal lesions of the liver. The accuracy, sensitivity, and specificity of lesion classification were 92.95%, 90.80%, and 97.44%, respectively. The proposed CAD system is fully automatic as no segmentation of region-of-interest (ROI) is required.

1. Introduction

Liver is the largest internal organ in the body. It neutralizes toxins, assists in the processing of proteins and fats from digested food, keeps important nutrients, and produces and secretes bile [1,2].

According to the American Cancer Society, liver cancer is the 8th leading cause of cancer related death in women and 5th in men worldwide [3]. The death rates due to liver cancer have tripled since the year 2000. One of the reasons is the lack of tools to detect early symptoms of the disease [4], and hence many patients are diagnosed with liver cancer in an advanced stage. Lesions of the liver are often found by chance during a routine check-up with ultrasound examination [5]. Thus, differentiating the lesion type at the time of diagnosis can be beneficial to the patients. Focal liver lesions can either be benign (non-cancerous) or malignant (cancerous). Examples of benign lesions are liver cysts, liver abscesses, hemangioma, focal nodular hyperplasia, and hepatic adenoma [6]. Malignant lesions are hepatocellular carcinoma (HCC), cholangiocarcinoma, biliary cystadenocarcinoma, and lesions from metastases (MET) originating from cancers in other organs [6]. Preexisting conditions such as fatty liver disease and cirrhosis can increase the risk of developing a liver cancer [7].

Histopathological examination (HPE) of a biopsy sample is the gold standard to characterize a liver lesion. However, biopsy is an invasive and costly surgical procedure. Ultrasound imaging has been used as a common diagnostic tool for initial diagnosis of the liver because it is non-invasive, non-ionizing and cost-effective. However, it is difficult for radiologists to determine the nature of the lesion based on the images alone. To overcome this shortcoming, we developed a computer-aided

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diagnosis (CAD) system to aid in the characterization of liver lesion using ultrasound images.

The literature review on the development of CAD systems to discriminate between the different liver lesions is scarce (see Table 1). Aside these papers, there are also CAD systems developed for fatty liver disease and cirrhosis [8]. Acharya et al. [9–12] investigated multiple techniques to develop a robust algorithm to assist in the early diagnosis of liver diseases such as fatty liver disease and cirrhosis. Having a CAD system to detect liver lesions at an early stage could be helpful in identifying the severity of the lesions, including cancer at earliest possible time [8].

Several authors have used contrast-enhanced ultrasound (CEUS) images for the identification of focal liver lesions [13–15]. A few CAD systems were also developed using CEUS images. Sugimoto et al. [16] and Shiraishi et al. [17] used CEUS images for the automated identification of focal liver lesions.

In this work, we proposed to develop an automated CAD system for the classification of liver lesions into normal, benign, and malignant classes using conventional ultrasound images. CEUS images were not considered in this work as the examination is invasive and involves additional costs to the patients. In most countries, CEUS is performed as the second-line imaging method after inconclusive baseline ultrasound for the diagnosis of benign focal liver lesions [18]. Fig. 1 illustrates the different types of focal liver lesions included in this study.

2. Data collection

This study was approved by the Medical Research Ethics Committee, University of Malaya Medical Centre, Malaysia (Protocol No. MEC 937.13). The liver ultrasound images and HPE results were retrieved retrospectively from the Radiological Information System and Electronic Medical Record system of the Department of Biomedical Imaging, University of Malaya Medical Centre, Kuala Lumpur, Malaysia. The data were collected for a period of 3 years, from the year 2014–2017, and included 463 ultrasound images from 101 patients (86 males, 15 females, aged 58.5 ± 15.1 years) to develop the CAD tool. Ultrasound imaging findings were validated with biopsies. Table 2 shows the total number of images (78 normal, 26 benign, and 36 malignant) used in each class.

3. Methodology

A graphical representation of the proposed technique is reflected in Fig. 2.

3.1. Pre-processing

The ultrasound images (256 × 256 pixels) were subjected to contrast limited adaptive histogram equalization (CLAHE) [25]. CLAHE works by enhancing to small tiles (8 × 8 pixels) and bilinear interpolation is used to combine neighboring tiles to remove boundaries, resulting in equalize intensity and improve contrast [26].

Subsequently, Radon transform and Top-hat filtering were applied.

3.2. Features extraction

The Bi-dimensional empirical mode decomposition (BEMD) [27] is then executed to extract features from the top-hat transformed liver images. BEMD is the 2-D extension of the empirical mode decomposition, which uses a sifting process which considers the neighbouring windows to detect extrema iteratively [28]. The sifting process uses radial basis function to connect the maxima and minima points, forming an 'envelope'.

The local mean is found by averaging 2 envelopes and deducted from the liver image to find the first intrinsic mode functions (IMF), and the process is repeated to extract other IMFs. The riding waves (oscillations with no zero-crossing between extrema) are removed, and uneven amplitude are smoothed by the sifting process.

The BEMD [29] extracts a 2-D finite number of oscillatory

Table 1
Selected published studies on the CAD system for focal liver lesions.

Authors, Year	Number of Images	Methodology		Segmentation of ROI	Performance (%)		
		Features	Classifier Used		Acc	Sen	Spec
Mittal et al. [19], 2011	N: 16 C: 17 H: 18 HCC: 15 MET: 45	• Textural	• NN	Yes	86.40	–	–
Virmani et al. [20], 2013a	HCC: 27 MET: 27	• Textural • GA-SVM	• SVM	Yes	91.60	–	–
Virmani et al. [21], 2013b	N: 21 C: 12 H: 15 HCC: 28 MET: 32	• Textural • PCA	• SVM	Yes	87.20	–	–
Virmani et al. [22], 2014	N: 21 C: 12 H: 15 HCC: 28 MET: 32	• Textural • PCA	• NNE	Yes	95.00	–	–
Hwang et al. [23], 2015	C: 29 H: 37 M: 33	• Textural • PCA	• ANN	Yes	<96.00	–	–
Manth et al. [24], 2016	H: 16 HCC: 28	• Textural	• SSVM	Yes	94.30	–	–
Present study	N: 78 B: 26 M: 36	• Radon transform • Top-Hat • Bi-EMD • ADASYN • PSO	• PNN	No (Fully-automated)	92.95	90.80	97.44

ROI = region of interest, Acc = accuracy, Sen = sensitivity, Spec = specificity, B = benign, C = cyst, H = hemangioma, HCC = hepatocellular carcinoma, M = malignant, MET = metastases, N = normal, GA-SVM = genetic algorithm-support vector machine, PCA = principal component analysis, ANN = artificial neural network, NN = neural network, NNE = neural network ensemble, SVM = support vector machine, SSVM = smooth support vector machine.