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Automated breast cancer detection and classification using ultrasound images: A survey

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ABSTRACT

Breast cancer is the second leading cause of death for women all over the world. Since the cause of the disease remains unknown, early detection and diagnosis is the key for breast cancer control, and it can increase the success of treatment, save lives and reduce cost. Ultrasound imaging is one of the most frequently used diagnosis tools to detect and classify abnormalities of the breast. In order to eliminate the operator dependency and improve the diagnostic accuracy, computer-aided diagnosis (CAD) system is a valuable and beneficial means for breast cancer detection and classification. Generally, a CAD system consists of four stages: preprocessing, segmentation, feature extraction and selection, and classification. In this paper, the approaches used in these stages are summarized and their advantages and disadvantages are discussed. The performance evaluation of CAD system is investigated as well.

1. Introduction

Breast cancer is the second leading cause of death for women all over the world and more than 8% women will suffer this disease during their lifetime. In 2008, there were reported approximately 182,460 newly diagnosed cases and 40,480 deaths in the United States [4]. Since the causes of breast cancer still remain unknown, early detection is the key to reduce the death rate (40% or more) [2]. The earlier the cancers are detected, the better treatment can be provided. However, early detection requires an accurate and reliable diagnosis which should also be able to distinguish benign and malignant tumors. A good detection approach should produce both low false positive (FP) rate and false negative (FN) rate.

Previously, the most effective modality for detecting and diagnosing is mammography [1,2]. However, there are limitations of mammography in breast cancer detection. Many unnecessary (65–85%) biopsy operations are due to the low specificity of mammography [5]. The unnecessary biopsies not only increase the cost, but also make the patients suffer from emotional pressure. Mammography can hardly detect breast cancer in adolescent women with dense breasts. In addition, the ionizing radiation of mammography can increase the health risk for the patients and radiologists.

Currently, an important alternative to mammography is ultrasound (US) imaging, and it shows an increasing interest in the use of ultrasound images for breast cancer detection [6–8]. Statistics showed that more than one out of every four researches is using ultrasound images, and the proportion increases more and more quickly [3]. Studies have demonstrated that using US images can discriminate benign and malignant masses with a high accuracy [9,10]. Use of ultrasound can increase overall cancer detection by 17% [11] and reduce the number of unnecessary biopsies by 40% which can save as much as $1 billion per year in the United Sates [12]. Breast ultrasound (BUS) imaging is superior to the mammography in the facts: (1) Since having no radiation, ultrasound examination is more convenient and safer than mammography for patients and radiologists in daily clinical practice [11,13,16]. It is also cheaper and faster than mammography. Thus, ultrasound is especially fit for the low-resource countries in different continents [153]. (2) Ultrasound is more sensitive than mammography for detecting abnormalities in dense breasts, hence, it is more valuable for women younger than 35 years of age [11,14]. (3) There is a high rate of false positives in mammography which causes a lot of unnecessary biopsies [10]. In contrast, the accuracy rate of BUS imaging in the diagnosis of simple cysts can reach 96–100% [9]. US imaging becomes one of the most important diagnostic tools for breast cancer detection. However, sonography is much more operator-dependent than mammography, reading ultrasound image requires well-trained and experienced radiologists. Even well-trained experts may have a high inter-observer variation rate, therefore, computer-aided diagnosis (CAD) is needed to help radiologists in breast cancer detection and classification [13]. Recently, several CAD approaches have been studied to minimize the effect of the operator-dependent nature inherent in US imaging [15],

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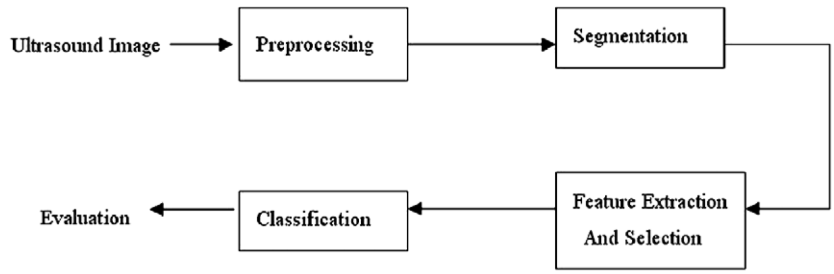

Fig. 1. CAD system for breast cancer detection and classification.

and to increase the diagnostic sensitivity and specificity [13,16]. As much as 65–90% of the biopsies turned out to be benign, therefore, a crucial goal of breast cancer CAD systems is to distinguish benign and malignant lesions to reduce FPs. Many techniques such as linear discriminant analysis (LDA), support vector machine (SVM) and artificial neural network (ANN) [5,10,17,18,20] have been studied for mass detection and classification. Most of the CAD systems need a large number of samples to construct the models or rules, but [22] proposed a novel diagnosis system requiring very few samples.

This survey focuses on summarizing the approaches for breast cancer detection and classification utilizing BUS images. Generally, the ultrasound CAD systems for breast cancer detection involve four stages as shown in Fig. 1.

(1) *Image preprocessing*: The major limitations of BUS imaging are the low contrast and interference with speckle [3]. The task of image preprocessing is to enhance the image and to reduce speckle without destroying the important features of BUS images for diagnosis.
(2) *Image segmentation*: Image segmentation divides the image into non-overlapping regions, and it will separate the objects from the background. The regions of interest (ROIs) will be allocated for feature extraction.
(3) *Feature extraction and selection*: This step is to find a feature set of breast cancer lesions that can accurately distinguish lesion/non-lesion or benign/malignant. The feature space could be very large and complex, so extracting and selecting the most effective features is very important. Most of the reported effective features are listed in Table 4.
(4) *Classification*: Based on the selected features, the suspicious regions will be classified as lesion/non-lesion or benign/malignant by various classification methods. The commonly used classifiers are discussed in Section 5.

Some CAD systems do not have image preprocessing and image segmentation components. In such a framework, only some texture features obtained directly from the images or ROIs are used as inputs of classifiers [13,16,20,22]. The advantage of such CAD system is its simple structure and fast processing speed, and disadvantage is that the features extracted directly from ROIs may not provide robust and accurate performance.

At last, we need to measure the performance of CAD systems. There is no a benchmark database of US images for comparing the performance of the algorithms/CAD systems, and it makes the evaluation of different CAD systems very difficult or even impossible. This indicates the necessity to build a benchmark BUS image base accessible to the public.

2. Preprocessing

The preprocessing of BUS images consists of speckle reduction and image enhancement. Speckle is a form of multiplicative noise generated by a number of scatterers with random phase within the resolution cell of ultrasound beam [33,34]. Ref. [29] has demonstrated that the k-distribution is a good model for the amplitude distribution of the received signal. A more generalized statistical model, the homodyned k-distribution, has been analyzed in [30]. It combined the features of the k-distribution and Rice distribution to better account for the statistics of the signal. To detect speckles, the parameters for the speckles should be estimated first. The speckle parameters of the k-distribution model can be estimated based on the moments [31]. An iterative method using the statistics of ultrasound signal is proposed to find the parameters of the homodyned k-distribution model [32]. Speckle makes the visual observation and interpretation difficult. Therefore, removing speckle without destroying important features for diagnosis is critical. Some speckle reduction techniques only work well on additive noise, and logarithmic compression is often employed to convert multiplicative noise into additive noise [33]. Image enhancement is used to improve the quality of low contrast images. We will review speckle reduction and image enhancement separately, however, many techniques can achieve both goals at the same time.

2.1. Speckle reduction

Speckle reduction techniques are classified into three groups: (1) filtering techniques [34–59]; (2) wavelet domain techniques [60–79]; and (3) compounding approaches [80–83].

2.1.1. Filtering techniques

Most filters are traditional techniques in spatial domain and can be categorized as linear and nonlinear filters.

2.1.1.1. Linear filters.

2.1.1.1.1. Mean filter. The mean filter [41,42] replaces each pixel by the average value of the intensities in its neighborhood. It can locally reduce the variance and is easy to implement. It has the effect of smoothing and blurring the image, and is optimal for additive Gaussian noise in the sense of mean square error. Speckled image is a multiplicative model with non-Gaussian noise, and therefore, the simple mean filter is not effective in this case.

2.1.1.1.2. Adaptive mean filter. In order to alleviate the blurring effect, the adaptive mean filters [35–40] have been proposed to achieve a balance between straightforward averaging (in homogeneous regions) and all-pass filtering (where edges exist). They adapt to the properties of the image locally and selectively remove speckles from different parts of the image. They use local image statistics such as mean, variance and spatial correlation to effectively detect and preserve edges and features. The speckle noise is removed by replacing it with a local mean value. The adaptive mean filters