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A hierarchical pipeline for breast boundary segmentation and calcification detection in mammograms

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ABSTRACT

Breast cancer is one of the most common cancer risks to women in the world. Amongst multiple breast imaging modalities, mammography has been widely used in breast cancer diagnosis and screening. Quantitative analyses including breast boundary segmentation and calcification localization are essential steps in a Computer Aided Diagnosis system based on mammography analysis. Due to uneven signal spatial distributions of pectoral muscle and glandular tissue, plus various artifacts in imaging, it is still challenging to automatically analyze mammogram images with high precision. In this paper, a fully automated pipeline of mammogram image processing is proposed, which estimates skin-air boundary using gradient weight map, detects pectoral-breast boundary by unsupervised pixel-wise labeling with no pre-labeled areas needed, and finally detects calcifications inside the breast region with a novel texture filter. Experimental results on Mammogram Image Analysis Society database show that the proposed method performs breast boundary segmentation and calcification detection with high accuracy of 97.08% and 96.15% respectively, and slightly higher accuracies are achieved on Full-Field Digital Mammography image datasets. Calculation of Jaccard and Dice indexes between segmented breast regions and the ground truths are also included as comprehensive similarity evaluations, which could provide valuable support for mammogram analysis in clinic.

1. Introduction

Breast cancer is one of the most common cancers among women [1]. Early detection of breast cancer has been shown to be associated with reduced breast cancer morbidity and mortality [2]. In clinics, various breast imaging techniques are used in the early diagnosis and screening of breast cancer, including ultrasound [3], Computed Tomography (CT) [4], Magnetic Resonance Imaging (MRI) [5] and mammography [6]. Mammography is low-energy X-rays imaging of the breast [7], which generates high-resolution images with high bit-depth, and provides the possibility of discovering abnormalities masked by surrounding and overlapping breast tissue [8]. Breast tissues are shown as pixel clusters of different intensities distributed in mammogram images, which mainly include fibro-glandular, fatty, and pectoral muscle tissues. Meanwhile, abnormal tissues including some ill-defined masses or calcification may appear as indicators of breast cancer or other breast diseases, which may also be shown in mammography. Although having limitations, mammography has a sensitivity of 85–90% for breast cancer detection [9]. As a proven and effective imaging modality, mammography remains the key screening tool for the detection of breast abnormalities [10].

In a mammography based Computer Aided Diagnosis (CAD) system, features of breast need to be quantified automatically to provide clinical evidences for human experts. A key part of mammography CAD is image segmentation which estimates skin-air boundary and pectoral-breast boundary which together define the breast contours. Existing studies of image segmentation, focusing on breast boundary and pectoral muscle segmentation, could be generally classified into 5 categories: thresholding, region-growing, morphology-based, active contour (AC) and texture-based according to their segmentation approaches. Global [11] or adaptive [12] thresholding methods are usually used to get the skin-air

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boundary because of significant intensity differences between the background and foreground tissues. However low contrast between pectoral muscle and the breast has limited the use of thresholding methods to get the pectoral-breast boundary. Chen et al. [13] proposes segmentation methods based on region growing by initializing 40 points along the mask boundary which is obtained by thresholding. Their results show the accuracy of pectoral-breast boundary detection is still lower than that of the skin-air boundary. Morphology-based methods [11,14] use the natural shape features to build complicated models to fit the objects of breast. The main problem of these model-driven methods is that a generalized shape model is not able to cover all the complex shapes shown in mammography. AC is also a widely used method to segment the breast by initializing a boundary and letting the initialized boundary to approach the actual breast boundary based on minimizing energy functions. However, some of edge-based AC methods [15–17] dealing with mammography only detect the skin-air line with pectoral muscle left in the breast region. Texture-based methods extract textures from images based on texture filters such as wavelet [18] or Gabor filter [19], and determine boundaries between objects based on significant texture changes. Rampun et al. [22] developed a hybrid method by combining a model-based approach and region-based AC which produced very good results but still less accurate when estimating pectoral muscle boundaries with complex contours.

In addition to the image processing approaches, another approach takes image pixels as individual samples and performed segmentation by labeling pixels into different categories. Some researches [20,21] firstly assign an initial label to each pixel in a mammogram image, and then adjust pixel labels based on energy changes in the Markov Random Fields (MRF) of pixels. The main difficulty of the pixel labeling approach is that they tend to generate unsmooth or discontinuous boundaries, which need post adjustment to find the natural smooth boundaries. Generally speaking, detection of breast boundaries is still a challenging task due to artifacts, homogeneity between the pectoral and breast regions, and low contrast along the skin-air boundary [22]. Abnormal tissues are usually shown on mammogram images with higher densities. Since density is one of the mammographic features that are related to breast cancer risk [23], the separation between glandular and other high density masses is important in characterizing breast tissues.

Furthermore, mammographic calcification is an important feature of invasive and *in situ* breast cancer [24], so the detection of calcification is another key step in mammographic analysis. Calcifications are always small in size and have no significant contrast to surrounding tissues in mammogram images, and the common idea of detection is using various filters to separate the inhomogeneous pixel clusters of calcification from surrounding tissues. A batch of filter-based approaches including gray level thresholding [25], Wavelet [26,27] and filter banks [28], but it is still challenging for calcification detection because of the small size and low contrast in low quality mammogram images. Therefore further research considering shape and appearance features is needed in order to improve both accuracy and efficiency of filter-based calcification detection.

In this paper, we propose an automated image processing pipeline, based mainly on pixel clustering without training, to estimate breast boundaries and characterize breast tissues concurrently, including skin-air boundary estimation, breast segmentation, and calcification detection. The main contribution of our study includes a pixel-wise clustering scheme plus post processing to segment the breast boundaries precisely, and a novel filter to detect calcifications, which is suitable for most of calcification shapes and sizes in practice.

The rest of the paper is organized as follows. In Section 2, we firstly describe the dataset used to evaluate the proposed method followed by explanations of the technical parts of this study such as detection of skin-air boundary, pectoral muscle to breast boundary segmentation, and calcification localization. In Section 3, experimental results are presented to show the performance of the proposed methods which covers both quantitative and qualitative evaluations. Finally, discussions on the proposed methods and further improvements are presented in the last Section.

2. Materials and methods

To deal with mammogram image segmentation more efficiently and robustly, an automated hierarchical pipeline including image preprocessing, breast segmentation, boundary detection and calcification localization is proposed, which is shown in Fig. 1. The spatial distributions of different tissues and abnormalities such as calcifications in breast can be extracted from the integrated pipeline, which makes it possible to focus on the region of breast and establish essential indicators for clinical references.

2.1. A. The dataset

Generally two kinds of mammography are being used in clinic, including analog Screen-Film Mammography (SFM) and Full-Field Digital Mammography (FFDM) [8]. Although it has been claimed that FFDM has more benefits than SFM [29], analysis of digitally scanned SFM still has realistic significances because comparisons are always needed between prior SFM and current digitalized mammography in many cases, and the processing methods of SFM could be directly applied on FFDM images with few adjustments. On the other hand, most of the mammogram digital datasets nowadays do not contain ground truth or annotations from expert radiologist which make it difficult for quantitative evaluation.

In our experiments we consider the Mammogram Image Analysis Society (MIAS) database, which is one of the first publicly released mammography datasets, MIAS contains the original 322 8-bit gray scale images of digitalized SFM at 50 μm resolution [30], and is associated truth data of breast boundary, character of background tissue and especially the locations of calcifications and various masses provided by expert radiologists. We also consider FFDM images with ground truths of segmentation. 100 images from the 8-bit Breast Cancer Digital Repository (BCDR) database [31] and 201 images from the 32-bit INbreast database [32] are selected for our experiments.

2.2. B. Gradient map for skin-air boundary

In quite a number of digitally scanned SFM images from the MIAS database, various artifacts have similar high intensities as the breast. To obtain the accurate skin-air boundary, we firstly calculated the weight for each pixel based on the gradient magnitude at that pixel using a 3×3 cross window, and returns the weight array (W). The weight of a pixel is inversely related to the gradient magnitude combining gradients of both vertical and horizontal direction at the pixel location, which separated higher intensity areas from low intensity background because sharp gradient magnitude changes occurred on the edges between foreground and background. Then, a horizontal line fitting strategy was applied to remove artifacts such as labels, markers, scratches, and even tapes which adhesive to the top of breast boundary as shown in Fig. 2(f).

As shown in Fig. 2, significant differences are along the skin-air line in the image without artifacts. Minor gradient weight noises could be easily removed by image erode techniques [33] as illustrated from the second column to the third, which erased thin lines and kept the main body of gradient weights. Only the largest body was kept as the breast plus pectoral region, and artifacts with smaller sizes were removed. Meanwhile, usually artifacts adhere to the breast break the smooth outline of breast boundary. A 2D curvilinear structure detection method [34] was used on the initial boundary line, which detected the inflection points with sharp changes of curvature, shown as red dots along the initial skin-air line in Fig. 2(i). Then, the tape could be cut off by a horizontal line from the lowest inflexion point based on the natural curves of breast. Closed line as the skin-air boundaries was then acquired as shown in the last column of Fig. 2. Adjusted mask of breast plus pectoral muscle could