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Medical breast ultrasound image segmentation by machine learning

Yuan Xu[a], Yuxin Wang[a], Jie Yuan[a,*], Qian Cheng[b], Xueding Wang[b,c], Paul L. Carson[c]

[a] Department of Electronic Science and Engineering, Nanjing University, Nanjing 210093, China
[b] Department of Physics, Tongji University, Shanghai 200000, China
[c] Department of Radiology, University of Michigan, Ann Arbor, MI 48109, USA

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ABSTRACT

Breast cancer is the most commonly diagnosed cancer, which alone accounts for 30% all new cancer diagnoses for women, posing a threat to women's health. Segmentation of breast ultrasound images into functional tissues can aid tumor localization, breast density measurement, and assessment of treatment response, which is important to the clinical diagnosis of breast cancer. However, manually segmenting the ultrasound images, which is skill and experience dependent, would lead to a subjective diagnosis; in addition, it is time-consuming for radiologists to review hundreds of clinical images. Therefore, automatic segmentation of breast ultrasound images into functional tissues has received attention in recent years, amidst the more numerous studies of detection and segmentation of masses. In this paper, we propose to use convolutional neural networks (CNNs) for segmenting breast ultrasound images into four major tissues: skin, fibroglandular tissue, mass, and fatty tissue, on three-dimensional (3D) breast ultrasound images. Quantitative metrics for evaluation of segmentation results including Accuracy, Precision, Recall, and $F1_{measure}$, all reached over 80%, which indicates that the method proposed has the capacity to distinguish functional tissues in breast ultrasound images. Another metric called the Jaccard similarity index (JSI) yields an 85.1% value, outperforming our previous study using the watershed algorithm with 74.54% JSI value. Thus, our proposed method might have the potential to provide the segmentations necessary to assist the clinical diagnosis of breast cancer and improve imaging in other modes in medical ultrasound.

1. Introduction

The purpose of this work was to segment the breast ultrasound images into all major functional tissues automatically. Breast cancer is one of the most common cancers accounting for 30% of cancer diagnoses in women, with increasing incidence in recent years [1]. It has become the leading cause of cancer mortality among women younger than 45 years old [2]. Ultrasound imaging is a widely employed imaging method to characterize breast masses [3] due to its avoidance of ionizing radiation, real-time visualization, relatively inexpensive price and non-invasive diagnosis [4]. Ultrasound imaging is also a tool for breast density assessment [5]. Breast density is often taken as a predictor of breast cancer risk assessment and prevention [6]. The percentage of breast density is calculated by dividing the area of the fibroglandular tissue by the total area of the breast. The odds ratio of developing breast cancer for women with most dense breasts is 2 to 6-fold greater than women with normal breast density [7].

Segmentation of breast ultrasound images could help radiologists discriminate different functional tissues, which provides valuable references on image interpretation, tumor localization, and clinical diagnosis of breast cancer. For breast density assessment, quantitative segmentation should be more consistent and precise than the qualitative approach where the analysis is limited by the reader's experience and training [5]. Moreover, different tissue properties have effects on the propagation of ultrasound waves. Segmentation of the bulk of the breast tissues could also facilitate correction of aberrations in those tissues and provide *a priori* information to improve ultrasound imaging in modes other than pulse echo, for example, transmission tomography and limited angle transmission tomography. With the source pulse modeled as a sinusoidal waveform of 0.5 MHz center frequency, Rungroj et al [8] enhanced limited angle tomography to produce speed of sound images by utilizing the image segmentations, and Hooi et al [9] applied a regularized least squares algorithm with data acquired at a center frequency of 3.75 MHz to construct the attenuation image by allowing inclusions of *a priori* information on major structures in the breast, such as the size and shape.

However, manual semantic analysis of breast ultrasound images is dependent on the theoretical basis and clinical experience of

* Corresponding author.
E-mail address: yuanjie@nju.edu.cn (J. Yuan).

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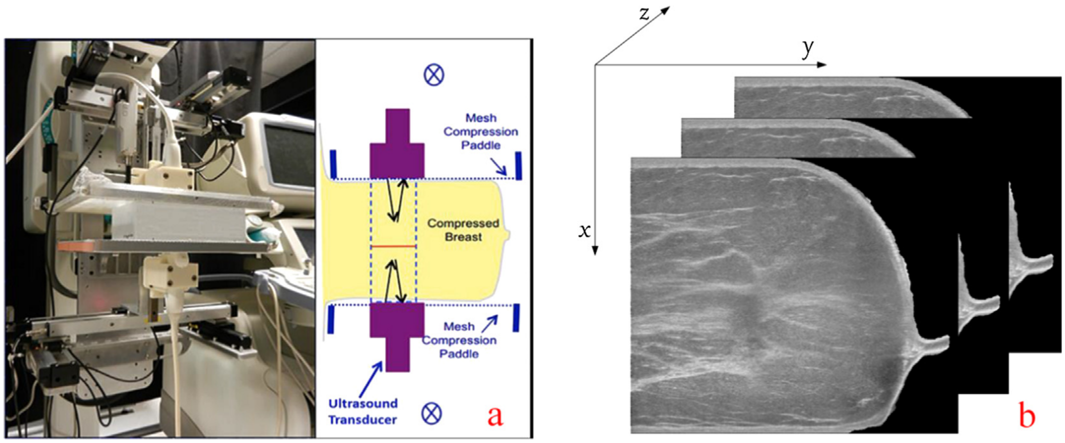

Fig. 1. (a) The BLUCI system; (b) 2D breast ultrasound image sequence.

radiologists, which results in subjective interpretation and inter-observer variability. Such manual analysis is also labor intensive and time-consuming for large scale clinical ultrasound images. To eliminate the operator dependency and reduce the burden on radiologists, the computer-aided detection (CAD) system, one of the major research subjects in medical imaging [10], could be utilized for automatic breast image segmentation [11]. Full breast segmentation is in contradistinction to the much more frequently studied detection and segmentation of breast masses. Among the studies focusing on automated segmentation of breast images in pulse echo ultrasound imaging, various segmentation algorithms have been proposed. These include threshold segmentation [12–14], the active contour model (ACM) [15–18], clustering algorithms [11,19–21], and some other methods [22–25]. Huang et al [16] proposed a method which used a watershed algorithm to obtain the initial active contour model first, and then minimized the energy function to accurately define the tumor boundary. Kekre et al [19] proposed another method for breast image segmentation, which used Vector Quantization (VQ) based clustering technique with Linde Buzo Gray (LBG), Kekre's Proportionate Error (KPE), and Kekre's Error Vector Rotation (KEVR) codebook generation algorithm followed by sequential cluster merging. Gu et al [24] used the Sobel operators on the morphological reconstructed images for edge information extraction to obtain gradient magnitude images and then used the watershed algorithm to demarcate all major tissues in 3D breast ultrasound volumes. However, ultrasound imaging has various inherent artifacts and noises [26,27], such as speckle noise [28], attenuation (absorption and scattering), blurry boundaries [29], and intensity inhomogeneity [27]. All of these artifacts increase the difficulty of the semantic analysis of breast ultrasound images. Furthermore, extraction of effective features for image interpretation is a challenging task, as well as the selection of parameters (e.g. thresholds). Thus, it is difficult to obtain promising and fully automatic segmentation results using existing traditional methods, where thresholds, features, and region of interest (ROI) are often hand-crafted and experience-determined.

Deep learning has emerged as a powerful alternative for supervised image segmentation in recent years [30]. Convolutional Neural Networks (CNNs) in the deep learning field have the ability to capture nonlinear mappings between inputs and outputs and learn discriminative features for the segmentation task without manual intervention. These features generated automatically through CNNs often outperform hand-crafted and pre-defined feature sets. In particular, CNN algorithms have been used to handle a variety of biomedical imaging problems, including medical image segmentation [30–32]. These studies have gained encouraging results, which indicates the potential of CNNs on medical breast image segmentation.

Conventional 2-dimensional (2D) segmentation may be affected by the limitations of 2D ultrasound imaging, such as suboptimal projection angle. 3D breast images can provide stereoscopic information and more image features, which is conducive to accurately distinguish different tissues. However, to classify a target pixel, 3D CNNs need to process a cubic input; this requires an increased number of network parameters, storage memories, and computation iterations compared with 2D CNNs. In our study, to incorporate 3D contextual information and reduce the computational burden of processing 3D ultrasound images, we propose a CNN-based method for breast ultrasound image segmentation on 3 orthogonal image planes. Specifically, the CNNs take image blocks centered at a pixel as inputs and produced the tissue class of the center pixel as the output. Taking the images segmented by clinicians as the ground truth, we trained the CNN models to distinguish skin, fibroglandular tissues, and masses. The segmentation process with the trained CNNs is completely automated without any human intervention. Visualization results showed that the proposed CNNs can demarcate all the major functional tissues consistent with the ground truth. When evaluated by the quantitative assessment metrics, we can yield satisfactory results of more than 80%, which indicate the value of our method in assisting breast cancer interpretation and diagnosis.

The paper is organized as follows: in Section2, the segmentation material and the method proposed are illustrated; in Section 3, the experimental results are presented; then, discussion and conclusion are given in Section 4.

2. Material and methods

2.1. Data acquisition

The 3D breast ultrasound images in this work were acquired by a dual-sided automated breast ultrasound imaging device at the Department of Radiology, University of Michigan, USA — the Breast Light and Ultrasound Combined Imaging (BLUCI) System. The BLUCI system allows for the acquisition of 3D ultrasound and photoacoustic volumetric imaging with the method analogous to classic mammography. The structure of the BLUCI system is shown in Fig. 1(a). A breast is fixed between two mesh compression paddles, two GE M12L transducers (GE Health Systems, Milwaukee, WI) with 12 MHz center frequency positioned above and below the paddles sweep across the breast with the scan parameters given by a control computer. Previously, solid paddles were used and the breast motion due to lubrication of the skin and paddle surface by the ultrasound coupling gel was counteracted by using an adhesive hair spray for acoustic coupling. With the mesh paddles, the 8 mm high rim compresses the retromammary fat trapping the rest of the breast that distends the mesh a few millimeters. There is a 2 mm displacement between the surface of the breast and the transducer when the transducer passes over the compressing membrane. As this is happening on each successive image