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● *Original Contribution*

A TWO-STEP SEGMENTATION METHOD FOR BREAST ULTRASOUND MASSES BASED ON MULTI-RESOLUTION ANALYSIS

Rafael Rodrigues,* Rui Braz,† Manuela Pereira,† José Moutinho,‡ and Antonio M. G. Pinheiro*

*Optics Center, Universidade da Beira Interior, Covilhã, Portugal; †Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã, Portugal; and ‡Faculty of Health Sciences, Universidade da Beira Interior, Covilhã, Portugal

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Abstract—Breast ultrasound images have several attractive properties that make them an interesting tool in breast cancer detection. However, their intrinsic high noise rate and low contrast turn mass detection and segmentation into a challenging task. In this article, a fully automated two-stage breast mass segmentation approach is proposed. In the initial stage, ultrasound images are segmented using support vector machine or discriminant analysis pixel classification with a multiresolution pixel descriptor. The features are extracted using non-linear diffusion, bandpass filtering and scale-variant mean curvature measures. A set of heuristic rules complement the initial segmentation stage, selecting the region of interest in a fully automated manner. In the second segmentation stage, refined segmentation of the area retrieved in the first stage is attempted, using two different techniques. The AdaBoost algorithm uses a descriptor based on scale-variant curvature measures and non-linear diffusion of the original image at lower scales, to improve the spatial accuracy of the ROI. Active contours use the segmentation results from the first stage as initial contours. Results for both proposed segmentation paths were promising, with normalized Dice similarity coefficients of 0.824 for AdaBoost and 0.813 for active contours. Recall rates were 79.6% for AdaBoost and 77.8% for active contours, whereas the precision rate was 89.3% for both methods. (E-mail: jrafael.ubi@gmail.com) © 2015 World Federation for Ultrasound in Medicine & Biology.

Key Words: **Breast ultrasound, Image segmentation, Image analysis, Scale-space analysis.**

INTRODUCTION

Breast cancer is one of the major causes of mortality among women, particularly in developed countries. It stands as the leading cause of female death by cancer, and the fifth overall. In 2008, 1.384 million new cases were diagnosed and 458,000 deaths registered (DeSantis et al. 2010). Nevertheless, a gradual decrease in breast cancer mortality has been noted, especially in developed or financially strong countries, where increased means of diagnosis are available. However, the number of cases worldwide continues to increase, and breast cancer is becoming the most prevalent cancer (DeSantis et al. 2010; Sant et al. 2006). Therefore, there is a need for effective diagnostic tools enabling prevention, monitoring and early detection of new cases.

Different imaging techniques are frequently used for breast cancer screening and diagnosis, including mammography, magnetic resonance imaging and ultrasound imaging (Cheng et al. 2010). Ultrasonography is a non-invasive, cost-effective and practically harmless technique that provides real-time diagnostic capability. Ultrasound can diagnose cysts with an accuracy near 100%, which helps to limit unnecessary biopsies (Madabhushi and Metaxas 2003). It is frequently used as a follow-up technique or as an adjunct to mammography in detection and diagnosis. Although mammography is currently the most widely used imaging method, breast ultrasound (BUS) imaging has been emphasized as a valuable tool for early cancer detection and diagnosis because of its attractive properties (Zhang et al. 2011). However, BUS images are typically characterized by speckle noise, shadows or other artifacts and poor edge definition, which are intrinsic to the imaging acquisition process and may result in a difficult and subjective analysis, even for experienced radiologists and oncologists (Fig. 1) (Noble and Boukerroui 2006;

Address correspondence to: Rafael Rodrigues, Rua Marques d'Avila e Bolama 6201-001 Covilhã, Portugal. E-mail: jrafael.ubi@gmail.com

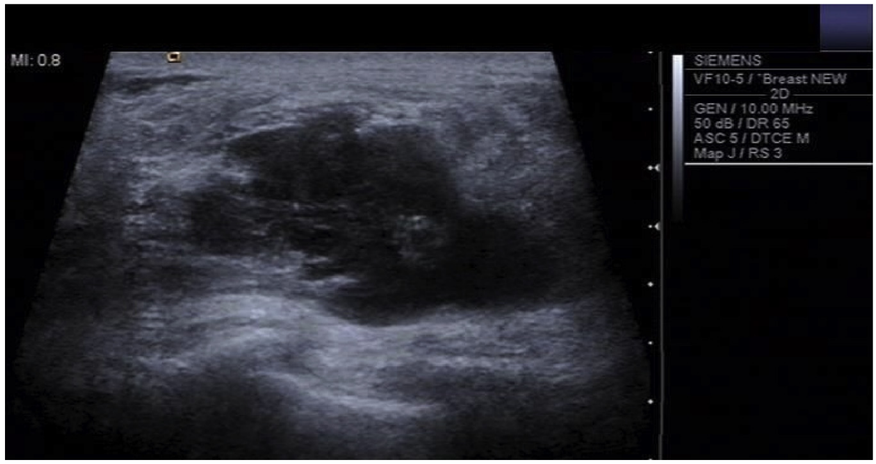

Fig. 1. Breast ultrasound (BUS) sample image.

Sehgal et al. 2006; Zhang et al. 2011). Therefore, computer-aided diagnosis (CADx) systems may become useful for both radiologists and oncologists. The development of such systems has attracted growing interest among researchers in this field.

The work described here focuses on the detection and segmentation of masses in BUS images. The images are pre-processed to deal with the constraints of typical ultrasound characteristics, and certain features obtained with the image processing techniques are used in the segmentation task. Typically, image segmentation is a difficult and complex task, which depends greatly on the type of image and may require large amounts of information to produce accurate and reliable results. However, under well-defined conditions, it is possible to obtain successful segmentation results, as described in Viola and Jones (2001), who performed facial recognition using an AdaBoost algorithm.

Several image segmentation methods have been proposed to respond to the challenging task of lesion segmentation in BUS images. Histogram thresholding is a fast and simple method that does not require training. It is one of the most often used segmentation techniques for monochromatic images. Histogram thresholding was used by Yap et al. (2008), with relative success, to identify lesion candidates and delimit lesions in BUS images. Other researchers have applied histogram thresholding to pre-processed images. Horsch et al. (2002) used median filtering and a Gaussian constraint function to reduce speckle prior to intensity thresholding. Chen et al. (1999) used a median filter along with the negative of a bidimensional Laplacian filter, which was used to enhance the contrast of meaningful elements. Despite its limitations, when applied to images with unimodal histograms, histogram thresholding allows simultaneous detection of multiple masses, as described by Joo et al. (2004). However, noise sensitivity associated with intensity histograms may lead to inaccurate results. Adaptive thresholding was tested in Yeh et al. (2005) and was highly correlated with manual segmentation. Also, the efficiency of the method in the presence of speckle noise was increased.

Model-based segmentation techniques have also been tested on BUS images. In Boukerroui et al. (2003), a Markov random field was applied with the focus on the adaptive features of the algorithm, which was controlled by a weighting function. The algorithm estimated iteratively the class parameters and assigned a class label to each pixel, considering local and global statistical measures. In another work (Xiao et al. 2002), Markov random fields were combined with maxima *a posteriori* in estimating the distortion field, which was followed by a multiplicative model and pixel labeling. The application of model-based algorithms is noise resistant and has some potential in BUS segmentation. Nevertheless, imaging models tend to break down in the presence of shadows, and the processes may become rather complex and time consuming (Cheng et al. 2010).

Other model-based approaches include deformable models such as active contours and level sets. Snake active contours have been applied to BUS segmentation with good results. In Jumaat et al. (2011), parametric active contour models such as gradient vector flow and balloon were used in BUS mass segmentation, after pre-processing with median filtering and histogram equalization. A segmentation refinement stage was designed, integrating curvature information or even empirical knowledge to improve the initial result. Another method described by Madabhushi and Metaxas (2003) relies on the automatic definition of seed points based on empirical knowledge given by radiologists. Region growing was then applied to obtain an initial contour.