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Estimation of the breast skin-line in mammograms using multidirectional Gabor filters

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ABSTRACT

Segmentation of the breast region is a fundamental step in any system for computerized analysis of mammograms. In this work, we propose a novel procedure for the estimation of the breast skin-line based upon multidirectional Gabor filtering. The method includes an adaptive values-of-interest (VOI) transformation, extraction of the skin–air ribbon by Otsu's thresholding method and the Euclidean distance transform, Gabor filtering with 18 real kernels, and a step for suppression of false edge points using the magnitude and phase responses of the filters. On a test set of 361 images from different acquisition modalities (screen-film and full-field digital mammograms), the average Hausdorff and polyline distances obtained were 2.85 mm and 0.84 mm, respectively, with reference to the ground-truth boundaries provided by an expert radiologist. When compared with the results obtained by other state-of-the-art methods on the same set of images and with respect to the same ground-truth boundaries, our method mostly outperformed the other approaches. The results demonstrate the effectiveness and robustness of the proposed algorithm.

1. Introduction

Breast cancer is the most common type of cancer and the main cause of cancer-related death among women globally [1]. Mammography is the most widely used method to screen asymptomatic women in order to reduce mortality due to breast cancer. Screening programs generate a large number of mammograms to be analyzed and interpreted by radiologists. The use of computer-aided detection (CADe) systems is becoming an effective strategy to reduce radiologists' workload and to assist them in efficient detection of breast cancer. Before being processed by a CADe system, mammographic images need to be processed in a preliminary stage in which the relevant radiographic regions are segmented from the remaining portions of the images. The breast skin-line bounds the area of the mammogram that is of interest for the detection of abnormalities. Several important tasks in computerized analysis of mammograms are strongly dependent on proper and reliable segmentation of the breast region, such as:

- Removal of labels and artifacts in screen-film mammograms (SFMs).
- Detection of the nipple as a stable reference point on a mammogram.
- Extraction of the fibroglandular disk to estimate breast density.
- Multiple-view analysis of mammograms for improved detection efficacy.
- Multimodality analysis of lesion characteristics.
- Alignment and subtraction procedures for bilateral comparison of mammograms.
- Registration of mammograms for content-based image retrieval.

Nonetheless, many inherent difficulties are encountered in developing automated systems which are capable of working correctly in every situation, some of which are listed below.

- The low contrast of the breast tissue near the skin–air boundary, which is mostly adipose, and appears noisy and dark.
- The tissue superimposition caused by 2D projection that may produce ambiguity in the image.
- The presence of noisy areas and artifacts that compromises image quality.

This paper addresses these open issues with the aim of developing a robust method able to estimate the breast skin-line in a diverse set of mammograms, including both SFMs and full-field digital mammograms (FFDMs). Before giving the details of the proposed

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approach, previous work dealing with automatic extraction of the breast skin-line in mammograms is reviewed, and a brief overview of the method is presented to illustrate the overall algorithm and its strengths.

1.1. Previous work

Several studies have addressed the problem of automatically detecting the breast boundary in mammograms. The early reported attempts were based on histogram thresholding and morphological filtering operations [2,3]. Despite the advantages of simplicity and convenience of these approaches, they were prone to errors due to a critical dependence of the result on the threshold selection process. The presence of background noise and artifacts also reduced the chances of obtaining an accurate estimate of the breast skin-line. Therefore, subsequent work considered further refinement procedures, applied to an approximate breast boundary extracted in a preliminary step, in order to improve the measures of acceptability of the results. Bick et al. [4] proposed a modified method for global histogram analysis followed by a combination of a gray-value range operator and region growing. Méndez et al. [5] divided the mammogram into three regions and used a tracking algorithm, consisting of gradient-based conditions applied to nine neighboring pixels at each point, to detect the border.

The first quantitative evaluation of segmentation results was provided by Ojala et al. [6]. In their work, a preliminary segmentation was performed using an adaptive histogram thresholding method and morphological filtering; the final breast boundary was then extracted by means of three different smoothing procedures: filtering in the Fourier domain, snakes, and B-splines. The best reported result, in terms of the mean error between the manually delineated and the automatically computed breast boundary, was achieved using the spline technique. The reported average error was 2.2 mm over 20 test images.

Ferrari et al. [7] used an active deformable contour model especially designed to be adaptive. The model was initialized by an approximate breast boundary obtained using the Lloyd–Max quantization method, morphological opening operators, and the chain-code method. The influence of this initial contour on the convergence of the algorithm was minimized by including a balloon force in the energy formulation. The reported average false-positive and false-negative rates were 0.41% and 0.58%, respectively, on a total of 84 mammograms.

A contour growing technique was proposed by Martí et al. [8] using scale-space edge detection with attraction and regularization terms. Their method was tested on 65 images from the MIAS database [9] providing mean correctness and completeness values of 0.97 ± 0.06 and 0.96 ± 0.06, respectively. In addition, 24 images from the DDSM database [10] were tested and average values of 0.95 ± 0.06 and 0.97 ± 0.01 were reported for correctness and completeness, respectively.

Raba et al. [11] used a region growing approach and tested their method over the whole MIAS database [9] obtaining a “near accurate” result for 98% of the mammograms.

Sun et al. [12] introduced the concept of dependency in distance from the stroma edge to the skin-line. The stroma edge was initially extracted by Otsu's thresholding method. A combination of adaptive thresholding and the greedy range selection method was used to estimate only the portion of the skin-line around the central nipple area. Due to the presence of background noise and artifacts, the missing upper and lower portions were extrapolated from the stroma edge using average Euclidean distances. They reported an average polyline distance measure (*PDM*) error of 3.28 pixels (0.66 mm) for 82 mammograms from the mini-MIAS database [9]. The same dataset was used to perform a quantitative comparison with the results obtained by Ferrari et al. [7], which yielded a mean *PDM* of 4.92 pixels (0.98 mm).

Yapa and Harada [13] developed a fast marching algorithm to track the evolution of the breast–skin interface by means of a partial-differential equation. They reported a 99.1% of accuracy in the segmentation results using 100 mammograms from the mini-MIAS database.

Karnan and Thangavel [14] applied a genetic algorithm to binary images of mammograms obtained by histogram thresholding. They evaluated the accuracy of the breast boundaries detected with their method using Pratt's figure of merit, which is an approximate indicator of edge quality, and obtained an average measure of 0.93 for 114 images.

Padayachee et al. [15] proposed a new method for selecting the optimal gray-level threshold by analyzing the areas enclosed by isointensity contours. The algorithm was tested on 25 mammograms yielding an average root-mean-squared error of 4.08 mm, using a preprocessing step based on the Lorentzian kernel.

In the work of Wu et al. [16], an initial breast boundary, obtained by dynamic thresholding, was refined by using gradient information from horizontal and vertical Sobel filtering. The accuracy of the breast boundary detection algorithm was evaluated on a total of 716 SFMs, by comparison with the reference boundaries drawn by radiologists. The reported Hausdorff distance was less than 4.8 mm for 94% of the images.

Silva et al. [17] used a dynamic programming algorithm by means of the definition of a cost function and reported an average *PDM* of 0.41 mm. Kus and Karagoz [18] developed a system to automatically detect the breast boundary by applying a multi-directional scanning window and constraints on the intensity and gradient pixel values. They reported average Hausdorff distance and *PDM* of 2.19 mm and 0.35 mm, respectively. The results reported by Silva et al. [17] and Kus and Karagoz [18] were obtained on the same set of 82 images used by Ferrari et al. [7] and Sun et al. [12].

Additional work on detection of the breast skin-line includes the use of region growing [19] and active contour [20–22] algorithms; however, the related reports presented only qualitative evaluation of the results.

It is important to note that in all of the works mentioned above, the performance of the algorithms was not evaluated on an independent test set of mammograms. This could lead to results which are dependent on the parameters chosen for the particular set of images. Another gap identified in this review concerns the lack of testing procedures for detection of the breast boundary on both SFMs and FFDMs. In fact, while digitized films are still encountered in clinical practice, FFDMs are gradually replacing SFMs, and the validation of a unique and robust procedure on both imaging modalities will benefit automated analysis of mammograms.

1.2. Overview of the proposed method

The proposed method combines the extraction of a skin–air ribbon obtained by Otsu's thresholding method [23] and the Euclidean distance transform (*DT*) [24] with edge detection by means of multidirectional Gabor filtering. Fig. 1 illustrates a flowchart of the whole procedure for identification of the breast skin-line. In order to overcome limitations related to the intrinsic variability between mammograms, a novel adaptive values-of-interest (VOI) logarithmic transformation is applied to the original image. The gray-level mapping is specifically designed to be adaptive and to enhance the skin–air interface on mammograms from different modalities, facilitating the detection of the breast boundary in the presence of variations in terms of contrast and noise. The image is then filtered with a bank of 18 Gabor filters equally spaced over the range $(-\pi/2, \pi/2]$. Gabor filters are used as