18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam 1996
4.4.1: Image Segmentation I - Model/Knowledge Based Methods

NONLINEAR FILTERING ENHANCEMENT AND HISTOGRAM MODELING SEGMENTATION OF MASSES FOR DIGITAL MAMMOGRAMS

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Abstract— **The objective of this study is to develop an efficient method to highlight the geometric characteristics of defined patterns, and isolate the suspicious regions which in turn provide the improved segmentation of objects. In this work, a combined method of using morphological operations, finite generalized Gaussian mixture modeling, and contextual Bayesian relaxation labeling was developed to enhance and segment various mammographic contexts and textures. This method was applied to segment suspicious masses on mammographic images. The testing results showed that the proposed method can detect all suspected masses as well as high contrast objects and can be used as an effective pre-processing step of mass detection with computer scheme.**

I. Introduction

Stochastic model-based image segmentation is a technique for partitioning an image into distinctive meaningful regions, based on the statistical properties of both gray-level and labeled images. Recently, this segmentation technique has received a considerable attention [1], [2]. However, a good segmentation result would depend on the suitable model selection for a specific image modality [3]. On the other hand, when the stochastic model is fixed, the segmentation result can also be improved by pattern-dependent enhancement techniques if the geometric characteristics of patterns is pre-defined. It is of great importance in medical image segmentation because the detection of subtle disease patterns should not be compromised by a technical inaccuracy [4].

Masses are commonly considered to be primary signs of breast cancer. It has been reported that approximately 50% of breast cancers detected radiographically demonstrate masses on mammograms [5]. The detection of masses is considered a difficult task for radiologists because the subtle difference between local dense parenchymal and masses. In this paper, we propose a pattern-dependent enhancement technique using morphological operations and a finite generalized Gaussian mixture (FGGM) model-based segmentation technique which will be described in detail below for its application to the segmentation of masses.

This work was supported in part by a NSF Grant MIP-9457397 and an U.S. Army Grant DAMD17-93-J-3007.

II. Methods

Based on the geometric properties of the contexts and textures in mammograms, we developed a two-step morphological filtering algorithm. The textures without the pattern information of interest are extracted by

$$r(i,j) = \max(0, [f(i,j) - (f \circ B)(i,j)]) \tag{1}$$

where $f(i,j)$ is the original image, $r(i,j)$ is the residue image between the original image and the opening of the original image by a specified structuring element B. Then, the regions of interests are enhanced by taking the difference between the original image and the specified rescaling transformation of the texture image

$$r_1(i,j) = \max(0, [f(i,j) - g(r(i,j))]) \tag{2}$$

where $g(\cdot)$ is the specified rescaling transformation.

The FGGM model is used to model the histogram of the image. The generalized Gaussian pdf given region k is defined by

$$p_k(x_i) = \frac{\alpha\beta_k}{2\Gamma(1/\alpha)} \exp\left[-|\beta_k(x_i - \mu_k)|^{\alpha}\right], \quad \alpha > 0 \tag{3}$$

where μ_k is the mean, $\Gamma(\cdot)$ is the Gamma function, and β_k is a parameter related to the variance σ_k by

$$\beta_k = \frac{1}{\sigma_k}\left[\frac{\Gamma(3/\alpha)}{\Gamma(1/\alpha)}\right]^{1/2}. \tag{4}$$

With different model parameter α, the model probability density function represents different distributions. Therefore, the FGGM is a good model for those images which statistical properties are unknown. The number of image regions K in the FGGM model can be determined by Akaike information criterion (AIC), minimum description length (MDL), and minimum conditional bias and variance criterion (MCBV) [2]. Once K is known, one can initialize model parameters using adaptive Lloyd-Max histogram quantization algorithm and estimate model parameters using expectation-maximization (EM) algorithm. Given a FGGM model, a contextual Bayesian relaxation labeling technique [6] is employed to perform image segmentation. Finally, we used binary morphological opening and closing operations to reduce all small objects which, as we knew previously, were not masses.

III. Results and Discussion

We have applied our method to mass detection. Five mammograms with masses were chosen as testing images. The areas of suspicious masses were located by an expert radiologist. The selected mammograms were digitized with an image resolution of $100\mu m \times 100\mu m$ per pixel by the Lumisys DIS-1000. For this study, we shrinked the digital mammograms by averaging 4×4 pixels into one pixel. It is applicable for mass cases.

In order to justify the suitability of morphological structural elements, the geometric properties of the contexts and textures in mammograms were studied. A disk with a diameter of 7 pixels was chosen as morphological structing element B to extract textures in mammograms. In the last stage of our approach, we applied morphological opening and closing filtering using a disk with a diameter of 5 to eliminate small objects.

According to previous investigator's work [7], the suitable number of regions, K, is 8 for most mammograms. In this work, we fixed $K = 8$, and changed the values of α for estimating the FGGM model parameters. We used global relative entropy (GRE) between the histogram and the estimated FGGM distribution as a measure of the estimation bias. We found that GRE achieved minimum distance when FGGM parameter $\alpha = 3.0$ as shown in Fig. 1. This indicated that FGGM model is better than finite normal mixture model ($\alpha = 2.0$), which has been mostly chosen in stochastic model-based segmentation, if the statistical properties of mammograms is not known.

With $K = 8$, $\alpha = 3.0$, we compared the segmentation results based on the enhanced mammograms with those based on the original mammograms. The results demonstrated that all the areas of suspicious masses in our tested mammograms were detected after enhancement. On the other hand, only parts of suspicious masses were detected with the original mammograms. In addition, some very subtle cases were undetected based on original mammograms. The undetect areas were mainly occurred at lower intensity side of the shaded objects which, however, extracted on morphological enhanced mammograms. Fig. 2 showed one of segmentation results with original mammograms and those of after morphological filtering-based enhancement of the original mammograms.

IV. Conclusions

This work is a part of our research in mammographic mass detection. The experimental results indicate that the segmentation of suspected masses can be affected by different K and α. With suitable K and α, the segmentation results can be significantly improved by the proposed pattern-dependent enhancement algorithm using morphological operations. Hence, morphological filtering combined with stochastic model-based segmentation is an effective way to extract mammographic suspicious patterns of interest, and thereby will facilitate the procedures of mammographic computer-aided diagnosis.

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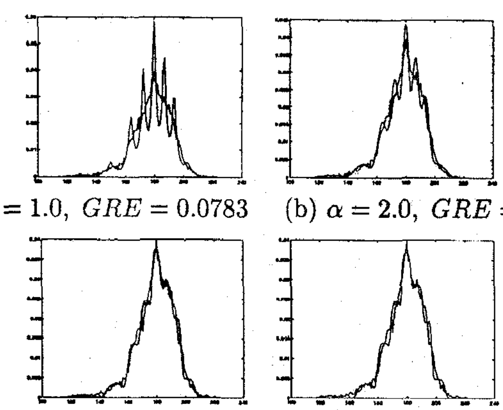
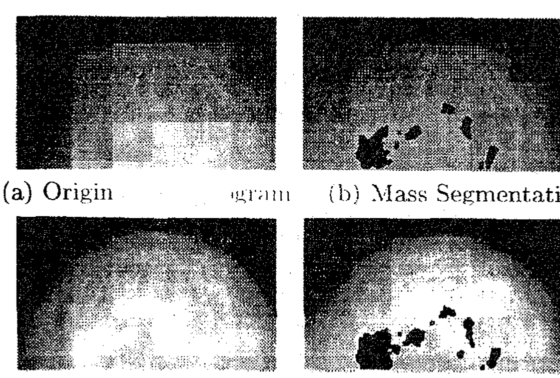


(a) $\alpha = 1.0,\ GRE = 0.0783$ (b) $\alpha = 2.0,\ GRE = 0.0369$

(c) $\alpha = 3.0,\ GRE = 0.0251$ (d) $\alpha = 4.0,\ GRE = 0.0282$

Fig. 1. The comparison of different learning curves and histogram of original mammogram, $K = 8$.



(a) Origin gram (b) Mass Segmentation

(c) Enhanced Mammogram (d) Mass Segmentation

Fig. 2. The comparison of segmentation results between original and morphological enhanced mammograms, $K = 8$, $\alpha = 3.0$.