

# Automatic Tissue Classification for High-resolution Breast CT Images Based on Bilateral Filtering

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## ABSTRACT

Breast tissue classification can provide quantitative measurements of breast composition, density and tissue distribution for diagnosis and identification of high-risk patients. In this study, we present an automatic classification method to classify high-resolution dedicated breast CT images. The breast is classified into skin, fat and glandular tissue. First, we use a multiscale bilateral filter to reduce noise and at the same time keep edges on the images. As skin and glandular tissue have similar CT values in breast CT images, we use morphologic operations to get the mask of the skin based on information of its position. Second, we use a modified fuzzy C-mean classification method twice, one for the skin and the other for the fatty and glandular tissue. We compared our classified results with manually segmentation results and used Dice overlap ratios to evaluate our classification method. We also tested our method using added noise in the images. The overlap ratios for glandular tissue were above 94.7% for data from five patients. Evaluation results showed that our method is robust and accurate.

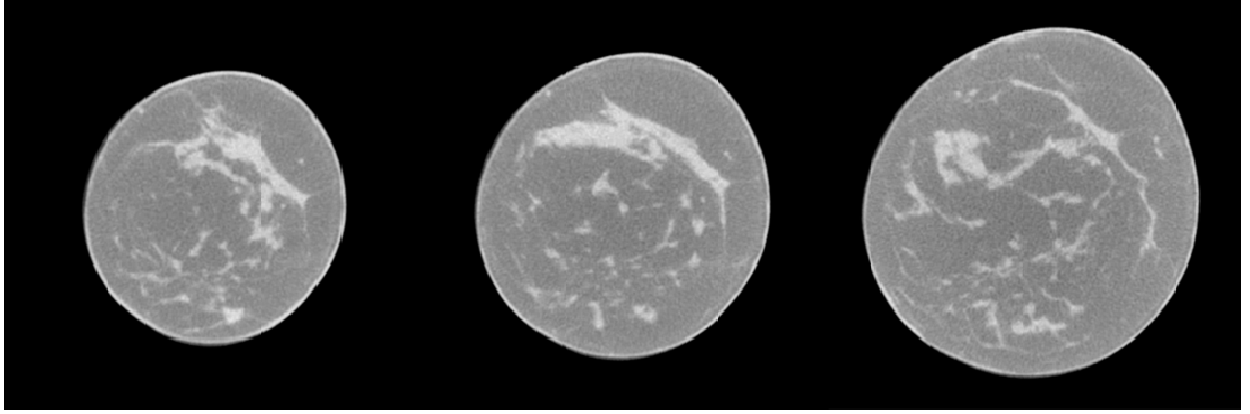
Keywords: Breast CT, bias correction, multiscale filter, fuzzy C-Mean classification, image classification, breast tissue classification, breast cancer

## 1. INTRODUCTION

In the US, the lifetime risk for women of developing breast cancer is one in eight [1]. Currently, the most common test for detection of breast cancer is mammography, but its two-dimensional nature results in tissue superposition, limiting its clinical performance, especially in women with dense breasts [2]. To overcome this limitation, extensive research is being performed in x-ray based tomographic imaging of the breast. One of the technologies being developed is dedicated x-ray breast computed tomography (breast CT) [3-5], which can eliminate the issue of tissue superposition. Breast CT images are acquired with similar methods to whole body CT, with major differences being the positioning of the patient relative to the x-ray source and detector, and the use of a half-cone x-ray beam which irradiates directly only the imaged breast. The resulting breast CT images consist of high-quality volumetric data that provide excellent visualization of the breast tissue distribution. Using breast CT images, an automatic breast tissue classification algorithm may be used to aid in the detection and diagnosis of breast cancer and for identification of women at high-risk of developing breast cancer. In this study we present an automatic breast tissue classification method that was tested using patient images acquired with a breast CT clinical prototype (Koning Corp., West Henrietta, NY) installed at Emory University's Winship Cancer Institute.

## 2. METHODS

Our classification method consists of three major steps: (1) The original breast CT images are corrected by an image-based bias correction method; (2) The corrected breast CT images are filtered using a multiscale bilateral filter; (3) The skin mask is obtained by a morphologic method; (4) A modified fuzzy C-mean classification method is applied to classify the filtered breast CT images.



**Figure 1.** Three breast CT image slices from one patient.

**Figure 1.** shows typical breast CT images. Because of CT X-ray beam hardening [6] and X-ray scatter, the resultant attenuation profile differs from the profile that would be obtained. This can result in a cupped appearance and degrade image quality [7]. We used an image-based method for automatic correction of this cupping artifact using a nonparametric coarse to fine approach [8] which allows cupping artifact to be modeled with different frequency ranges without user supervision. We defined an entropy-related cost function based on the combination of intensity and gradient image features. Bilateral filtering can remove noise at intra-regions while preserving the inter-region edge. The filtering process is a weighted average of the local neighborhood samples, where the weights are computed based on radiometric distance between the center sample and the neighboring samples. Bilateral filtering can be described as follows [9]:

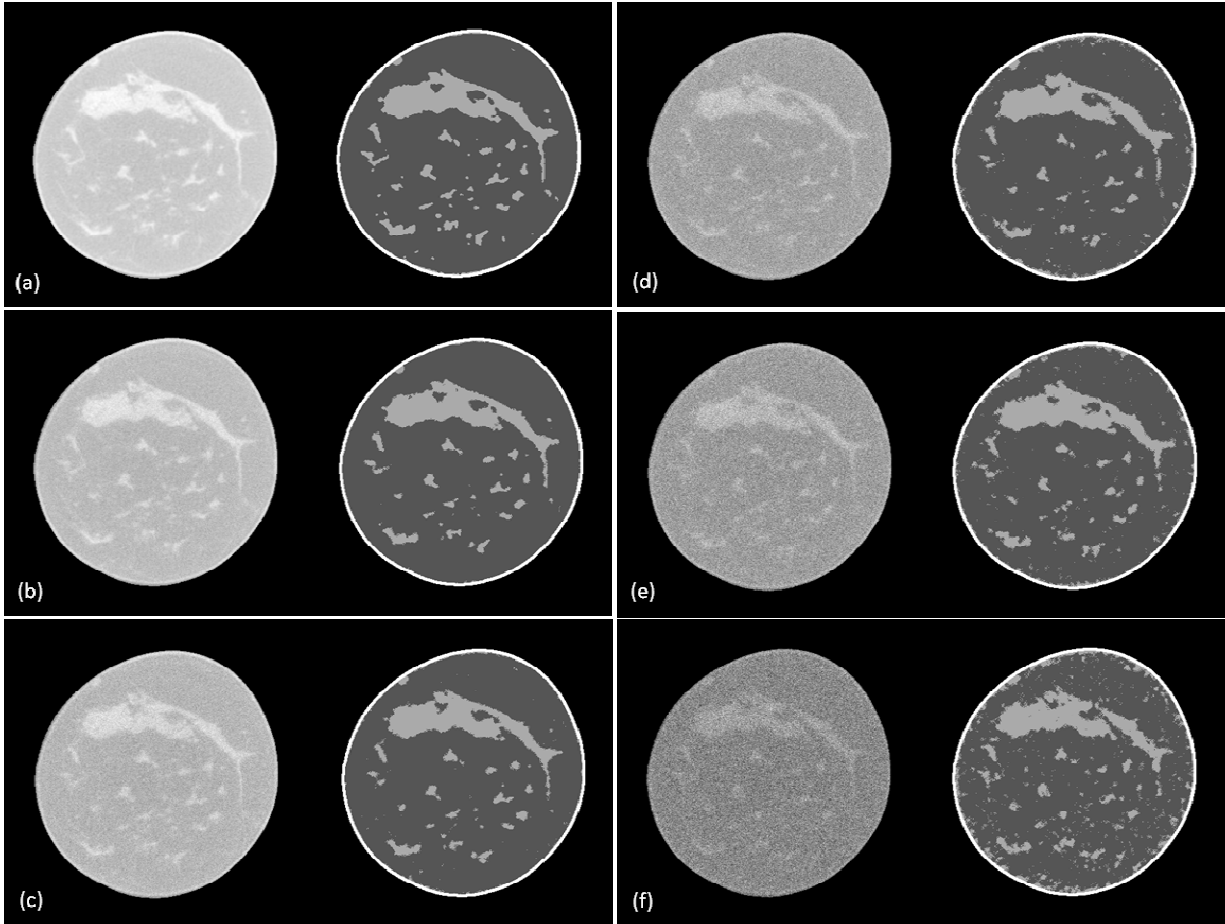
$$h(x) = \lambda^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(\xi) W_{\sigma_s}(\xi - x) W_{\sigma_r}(I(\xi) - I(x)) d\xi$$

$$\lambda(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_{\sigma_s}(\xi - x) W_{\sigma_r}(I(\xi) - I(x)) d\xi$$

Where  $I(x)$  and  $h(x)$  denote input images and output images.  $W_{\sigma_s}$  measures the geometric closeness between the neighborhood center  $x$  and a nearby point  $\xi$ ; and  $W_{\sigma_r}$  measures the photometric similarity between the pixel at the neighborhood center  $x$  and that of a nearby point  $\xi$ . Thus, the similarity function  $W_{\sigma_r}$  operates in the range of the image function  $I$ , while the closeness function  $W_{\sigma_s}$  operates in the domain of  $I$ . It smoothes images while preserving edges by means of a nonlinear combination of nearby image values. The range Gaussian is an edge-stopping function [10]. We reduce the width of the range Gaussian and increase the width of the spatial Gaussian at every scale to filter breast CT images. In our studies we used three scales.

In breast CT images, skin and glandular tissue have similar CT values [11], making them difficult to differentiate based only on the intensity information. Therefore, we use position information to classify the skin and glandular tissue. It has been reported that the skin thickness is  $1.45 \pm 0.30$  mm [12,13]. We can calculate the voxel for the skin based on the resolution of the breast CT images. In our studies, the breast CT voxel size is  $0.273 \times 0.273 \times 0.273 \text{ mm}^3$ , so we constrain the skin thickness to seven voxels. We use a threshold to get the mask for the whole breast and then use a  $7 \times 7$  box to

perform erosion operations in order to get the mask for the tissue within the skin, i.e. the fatty and glandular tissue. By subtracting the fatty and glandular tissue from the mask of the whole breast, we are able to get the mask for the skin. We use a modified fuzzy C-means (FCM) algorithm to classify the breast CT images [14,15]. Based on the two masks, we perform two classifications, one for the skin and the other for the fatty and glandular tissue.



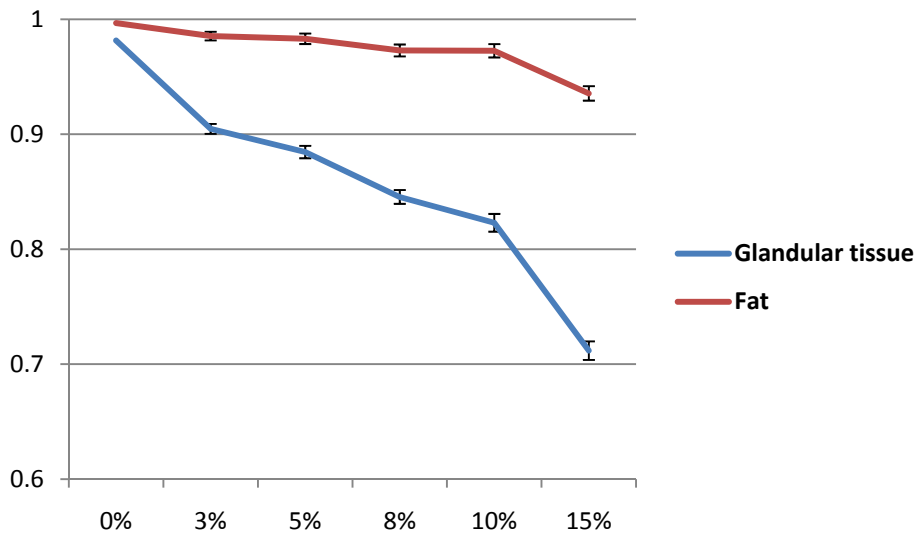
**Figure.2** Classification results of breast CT at different noise levels. (a) The original breast image and the classified result. (b)-(f) CT images with added 3%, 5%, 8%, 10% and 15% noise, respectively, and the corresponding classified results.

We validated the classification using a variety of evaluation and analysis methods [16,17,19-21]. In order to evaluate the performance of the classification method, the difference between the classified and manually segmented results was computed using the Dice coefficient [18]. In order to evaluate robustness of our method we added different levels of Gaussian noise to the breast CT images and repeated the classification.

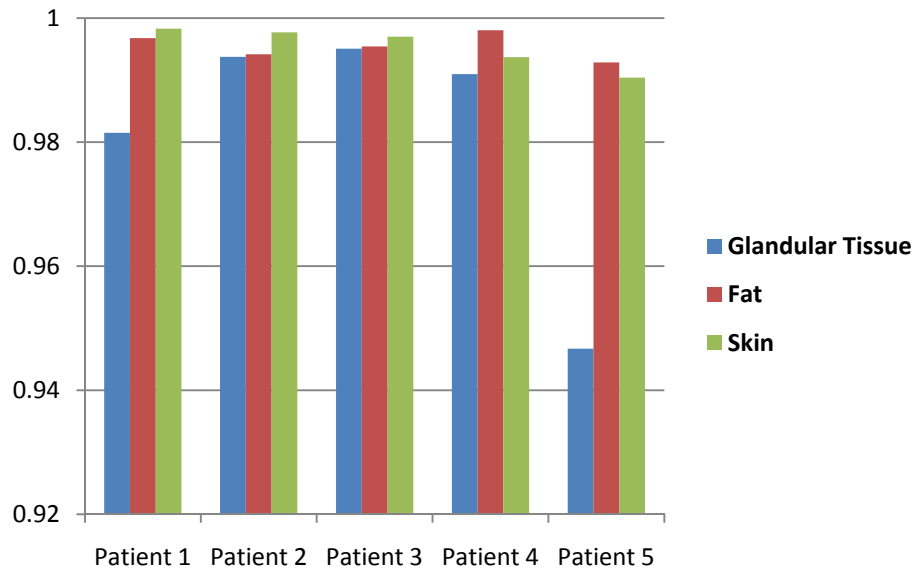
### 3. RESULTS

Figure 2 illustrates the visual assessment of the classification results of a breast CT image at different noise levels. The standard deviation of the Gaussian noise is 3%, 5%, 8%, 10% and 15% of the maximum intensity of the CT image. Figure 3 shows the Dice overlap ratios between the manually segmented results of original CT images and our classified results with different noise levels. The overlap ratio is over  $82.9 \pm 0.7\%$  when the original image was added with noise at the 10% level of the maximum CT intensity in the images. The method is robust for noisy images up to 10% added noise.

The classification method has been evaluated with five patient images. Each patient had different percentages of glandular tissue in the breast. We randomly selected three slices for each patient and manually segmented the images using a multi-threshold method to evaluate our classification results. Figure 4 shows the classification evaluation results of the five patients. The overlap ratios were more than 94.7%. Figure 5 illustrates the visual assessment of the classification results on breast CT images with 8%, 11% and 34% glandular tissue.



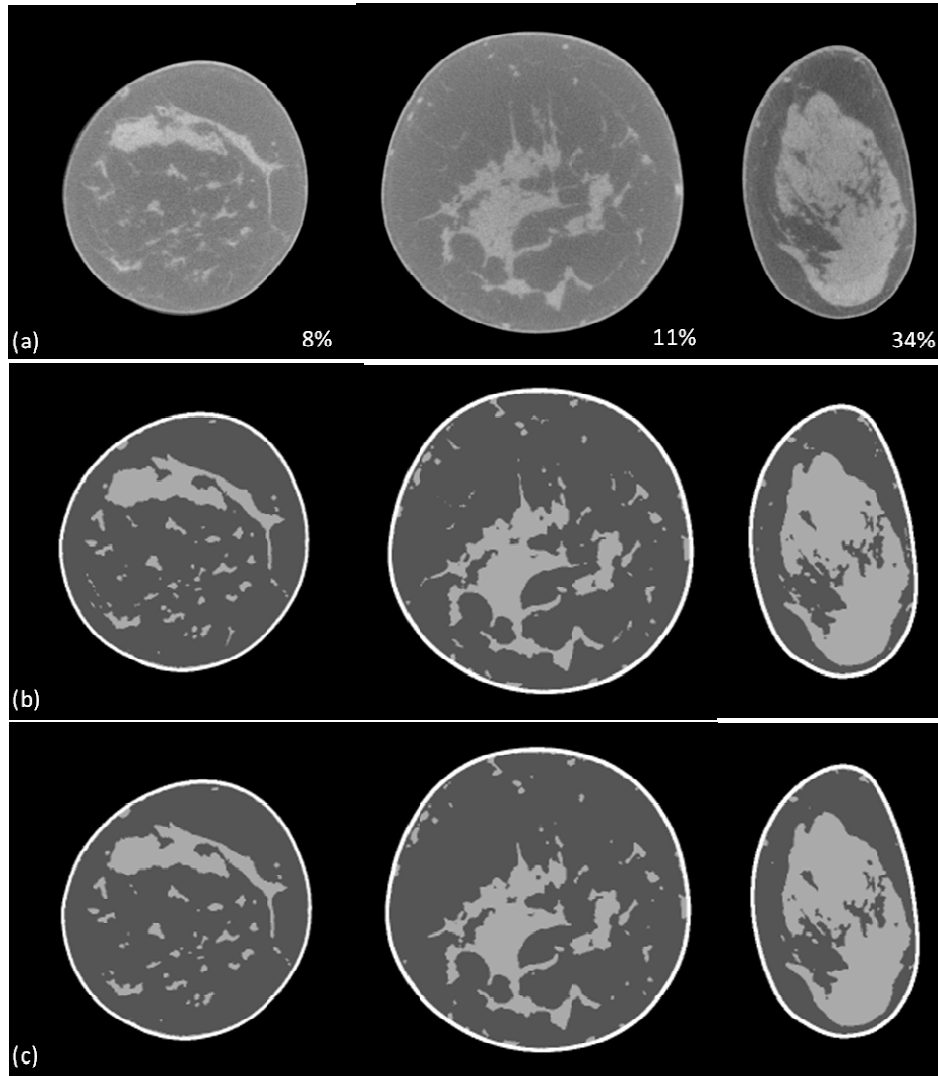
**Figure.3** Overlap ratios of the classification at different noise levels.



**Figure. 4** Overlaps ratios of glandular, fat and skin tissue for five patients.

#### 4. DISCUSSIONS AND CONCLUSIONS

We proposed a classification approach for dedicated high-resolution breast CT images to classify breast tissue into three primary constituents of skin, fat and glandular tissue. A multiscale bilateral filter was designed to process the breast CT images before classification. We compared our classified results with manual segmented results. Evaluation results demonstrated the accuracy and robustness of this method for breast CT image classification. Breast tissue classification from CT images can provide quantitative measurements for breast tissue composition, tissue density and distribution with respect to ages, which may be used for breast cancer detection and diagnosis and identification of high-risk patients.



**Figure. 5** Classification results of breast CT images of three patients (a) Breast CT images of three patients who had a different percentage of glandular tissue (8%, 11%, and 34%). (b) Manual segmented results. (c) Our classified results.

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