A Multiscale Algorithm for Segmenting Calcifications From High-Resolution Mammographic Specimen Radiographs

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We have developed a multiscale algorithm for segmenting breast calcifications from high-resolution specimen radiographs. The algorithm was evaluated using 152 mammographic regions of interest digitized at a 15- μ m spatial resolution. The true-positive detection rate was approximately 97.4% with 0.67 false-positives per image, and the segmentation error of individual calcification particles was approximately 5%. The performance of the algorithm is highly satisfactory.

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BREAST SPECIMEN radiographs exposed using nonscreen film have an inherent resolution of at least an order of magnitude greater than that of preoperative mammograms produced with the conventional film-screen technology. Computer analysis of such high-resolution images is a promising approach to the computer-assisted differential diagnosis (CADD) of breast calcifications. To make a full use of these radiographs, we digitize them at a high 15- μ m spatial and 10-bit intensity resolution.

These high-resolution images present unique challenges for the segmentation algorithm, including the high variation of the size and contrast of the calcification particles and the high variation of the background tissue characteristics. The previously developed segmentation algorithms^{1,2} are not quite suitable, since they were developed for use with preoperative low-resolution mammograms. In this report, we present a fully automatic algorithm for segmenting breast calcifications from digitized high-resolution specimen radiographs.

SEGMENTATION ALGORITHM

To produce an approximately constant noise level within all intensity levels, we first apply an

isointensity transform^{2,3} to the raw digitized images. Next, we identify the radiographically low-density regions, since they often contain noise that is locally very similar to calcifications. These regions are removed by segmenting the image with an adaptive threshold (Fig 1).

$$T = \begin{cases} \mu + \sigma \frac{s}{2} & \text{if } s \geq 0.5 \\ \mu + \sigma \frac{s}{2} - \sigma \left(1 - \frac{s}{0.5}\right) & \text{if } 0 < s < 0.5 \\ \mu - \sigma & \text{if } s \leq 0 \end{cases} \quad (1)$$

where the skewness,

$$s = \frac{1}{N} \sum_{i=0}^{N-1} \left(\frac{i - \mu}{\sigma} \right)^3$$

of the image histogram is used to identify the images that have a large amount of low-density pixels and require a high threshold for a satisfactory segmentation.

The regions that probably contain calcifications are identified using an approximate multiscale detection algorithm (Fig 2). Five scale images are generated by subsampling every N th pixel ($N = 1, 2, 4, 8, 16$) of the local mean image. The actual detection is performed using a difference-of-Gaussians procedure similar to Dengler et al⁴: after suppressing the large-scale background variation with a 15×15 low-pass Gaussian, the resulting difference image is convolved with a 5×5 bandpass Gaussian:

$$d_c(i, j) = \max \{0, I(i, j) - (I(i, j) * G_{bg}) * G_{bnd}\} \quad (2)$$

Next d_c is thresholded by

$$T_d = \begin{cases} \mu + t\sigma & \text{if } t\sigma > 0.2(M - \mu) \\ \mu + 0.2(M - \mu) & \text{otherwise} \end{cases} \quad (3)$$

where t is a sensitivity parameter, and μ , σ , and M are the mean, standard deviation, and maximum intensity of d_c . The use of M improves the segmentation in some special cases. Next, we restore the original scale of the segmented regions by upsampling them accordingly, and combine them into one binary image.

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Fig 1. Top: Original images. Bottom: Low-density region (black) removed from the active image region (white).

The precise segmentation algorithm (PSA) is applied repetitively to each detected region, R_i , while a new valid calcification, c , can be found (Fig 3). At each call, we first select the point of highest intensity within $R_i^j = R_i \setminus \bigcup_{k=1}^j C_{ik}$ as the seed pixel. The boundary of the calcification c that originates from the seed is the iso-intensity contour maximizing the Bayesian probability

$$P(R_i|c) = P(c|R_i)P(c) \quad (4)$$

where the apriori probability, $P(c)$, is dependent on the relative area covered by the isocontour, and the likelihood, $P(c|R_i)$, is the average of the normalized mean intensity, mean gradient, and minimum and maximum unit gradient of the isocontour representing c . The details of the algorithm have been presented elsewhere.⁵

RESULTS

The test images were produced by slicing biopsy specimens of 50 cases with calcifications into 5-mm thick serial slices that were imaged at 14 ± 1 kV on a high-resolution film. The 152 regions of

Fig 2. A region of interest with calcifications (left), and the approximately detected calcifications (right).

interest containing calcifications were digitized from the radiographs at 15- μ m spatial and 10-bit intensity resolution. The size of each digitized region was $1,275 \times 1,024$ pixels.

The accuracy of the segmentation produced by the PSA was evaluated by segmenting 90 calcification particles of varying image quality both manually and by the PSA. The resulting binary shapes were measured using five shape features (elongation,⁶ compactness,⁶ a localization measure [LOC],⁵ a fractal dimension measure [FDM],⁵ a Fourier descriptor measure [FF]⁷) that characterize the overall shape and boundary ripple of the calcification and are used in our CADD system. The results (Table 1) are shown for the case where the target region was smoothed by 3×3 averaging before applying the PSA.

The detection performance (Table 2) was evaluated by comparing each segmented image side by side with the original digitized image and the corresponding film radiograph. Each four-connected segmented region containing at least one calcification was labeled as true-positive. The few cases in which it was not possible to determine if the detected object was a true- or false-positive were labeled as false-positives. We also experimented with lower and higher sensitivity levels than those shown in the table, but the results were not satisfactory regarding the subsequent diagno-

Fig 3. PSA is applied repetitively to the detected region, while new calcifications can be found.

Table 1. Relative Mean Difference Between Feature Values Measured From Shapes Segmented Manually and by the PSA, Classified According to Visually Perceived Difficulty of the Segmentation Task

Feature	Easy	Medium	Hard
Elongation	2%	2%	2%
Compactness	3%	1%	5%
LOC	0%	0%	4%
FDM	2%	5%	5%
FF	0%	0%	1%

NOTE. Each class contains 30 calcifications.

sis: lower sensitivity resulted in missing some major calcifications, while higher sensitivity resulted in a few false-positives and overlapping particles. The result at the bottom row of Table 2 was computed for the complete segmentation algorithm, including the detection and precise segmentation of the calcifications with associated checks.

The major sources of the false-positives were film defects and small regions of high-density parenchyma with sharp contrast to the surrounding dark background. It is possible to identify and remove these false-positives, but their similarity to

Table 2. Detection Results as a Function of Sensitivity Parameter (t)

t	Findings	TP	FP	FP/Image
5.250	3,714	95.2%	4.8%	1.23
5.625	3,290	95.8%	4.2%	0.95
6.000	2,930	97.1%	2.9%	0.59
5.625*	3,723	97.4%	2.6%	0.67

*Result includes the precise segmentation with associated checks.

Abbreviations: TP, true-positive; FP, false-positive.

subtle calcifications would result in also removing a few true-positives.

CONCLUSION

We have presented a fully automatic algorithm for segmenting breast calcifications from high-quality specimen radiographs. The average segmentation error of a calcification particle with respect to common shape features is within 5% of the visually perceived calcification. The detection sensitivity and specificity of the complete algorithm are highly satisfactory.

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