Extraction of Microcalcifications in Digital Mammograms Using Regional Watershed

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In this report, a novel technique is proposed for computer-aided automatic extraction of microcalcifications in a digital mammogram. First, the microcalcifications are detected by morphological filtering, followed by entropy-based thresholding. Next, the microcalcifications are segmented by computing regional watershed. The proposed automatic technique is designed to serve as a visual aid to radiologists. Its efficacy is demonstrated through experimental results.

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BREAST CANCER is a major disease in women all over the world. Early detection is the most successful method of dealing with this disease. Microcalcifications are important early indicators of breast cancer. In digital mammograms, they appear as bright arbitrary-shaped regions. It is often difficult to detect small-sized microcalcifications in a nonhomogeneous background. Hence, there is a great need of an effective microcalcification detection algorithm for reliable diagnosis of breast cancer. Several techniques have been proposed for detection by filtering the background^{1,2} and segmentation of microcalcifications.³ Two most recent filtering techniques are (1) computation of the difference between the original and *dilated* image,¹ and (2) obtaining the difference between the original and *opened* image.² However, these filtering techniques are not efficient, as they still retain a significant amount of background structure. For segmentation of microcalcifications, a scheme employing watershed is proposed in Betal et al,³ but it requires manual adjustment of thresholds.

In this report, an efficient methodology for extraction of microcalcifications is proposed. The grayscale morphological opening operation is performed to eliminate the microcalcifications in the original mammographic image and retain only the background. This is followed by filtering, in which the difference between the original image and the grayscale reconstruction of the opened image is computed. The filtering results in an image in which the background is highly suppressed. Entropy-based automatic thresholding is then used to detect the microcalcifications. Finally, the microcalcifications are segmented by obtaining the watershed of the inverted original mammographic image,

Fig 1. Flowchart for filling all the catchment basins except the one at the current marker position, (x_1, y_1) .

with the detected locations of microcalcifications as markers.

DETECTION OF MICROCALCIFICATIONS

Let I be the original mammographic image and J be the image obtained after morphological opening of I . Thresholding of both I and J is performed successively for each gray level $k \in [1, N]$, where $N = 255$ is the maximum gray level of the image. Let I_k and J_k be the binary images obtained after thresholding I and J at gray level k , respectively. J_k is called the k th marker image and I_k is the

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0897-1889/00/1302-1030\$10.00/0

doi:10.1053/jdim.2000.6845

Fig 2. Original image showing microcalcifications.

Fig 3. The difference between Fig 2 and its opened image.

Fig 4. Difference between Fig 2 and its morphological reconstruction.

Fig 5. Markers obtained after entropy-based thresholding of Fig 4 and then assigning a pixel for each detected microcalcification.

corresponding mask. The elementary geodesic dilation of J_k within I_k by a disk-shaped structuring element H of unit radius, is given by

$$\delta_{I_k}^{(1)}(J_k) = (J_k \oplus H) \cap I_k \quad (1)$$

Next, the binary reconstruction $\rho_{I_k}(J_k)$ of mask I_k from the marker J_k is obtained by iterating the elementary geodesic dilation of J_k within I_k as follows.

$$\rho_{I_k}(J_k) = \lim_{n \rightarrow \infty} \delta_{I_k}^{(n)}(J_k) \quad (2)$$

Thus, the binary reconstruction operator progressively floods the connected components of I_k , whose intersection with J_k is nonempty. In other words, it simply extracts the connected components of I_k , which are marked by J_k . Next, we obtain the grayscale reconstruction⁴ of I from J using binary reconstructions $\rho_{I_k}(J_k)$ for $1 \leq k \leq N$. Let the grayscale reconstruction of image I from J be $\rho_I(J)$. The value of the pixel, p , in $\rho_I(J)$ is given by

$$\rho_I(J)(p) = \max \{k \in [0, N] | p \in \rho_{I_k}(J_k)\} \quad (3)$$

Fig 6. Segmented microcalcifications.

The grayscale reconstruction, $\rho_I(J)$, contains only the background structure of I . Therefore, a significant amount of background structure is filtered out by computing the difference between I and $\rho_I(J)$. Finally, entropy-based thresholding⁵ is applied on the difference image to detect the microcalcifications. A 1-pixel marker is assigned to each of the detected microcalcifications.

WATERSHED TRANSFORMATION

In this section, we describe the methodology of extraction of microcalcifications using regional watershed. Consider the inverted original mammographic image, I' , on which microcalcifications appear as dark spots on a bright background. If we imagine the image I' as a topographical surface, the microcalcifications appear as catchment basins. Our objective is to obtain the contours of the catchment basins at the marker positions obtained earlier as mentioned in the previous section.

In our proposed watershed algorithm, we obtain the watershed of each catchment basin one by one.

In brief, the approach is to first fill all the catchment basins except the one at the current marker position, and next obtain the watershed of the one unfilled catchment basin. The flowchart in Fig 1 describes the proposed methodology for filling all the catchment basin except the one indicated by the current marker.

EXPERIMENTAL RESULTS

The mammographic database provided by the Mammographic Image Analysis Society (MIAS) is used in the experiments. Each image in the database is of size $1,024 \times 1,024$ pixels with a dynamic range of 8 bits. Figure 2 shows a section of size 280×280 pixels obtained from a mammographic image. Figure 3 is the image obtained after computing the difference between the original image and its morphological opening. It can be observed that still a significant amount of background is present in the image. Figure 4 shows the difference between the original image and its grayscale reconstruction from the opened image. It is observed in Fig 4 that most of the background is filtered out, leaving behind only the calcifications. Figure 5 shows the markers obtained after entropy-based thresholding, with each region of the calcification represented by 1-pixel marker. Figure 6 shows the segmented microcalcification obtained after the proposed regional watershed using the markers.

CONCLUSION

An efficient computer-aided technique for automatic detection and extraction of microcalcifications in a digital mammogram is presented. The technique employs morphological filtering to suppress the background tissue significantly. The entropy-based thresholding is highly accurate, as it detects even subtle microcalcifications. The proposed watershed yields very good segmentation results by preserving the size and shape of microcalcification.

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