AUTOMATED DETECTION OF BREAST TUMOR

S. Mei Lai, Xiaobo Li, Walter F. Bischof

Department of Computing Science
University of Alberta
Edmonton, Alberta T6G 2H1

ABSTRACT

Mammography is an effective method for detecting breast cancer at the earliest possible stage. Mass screening of mammograms requires the development of automated systems to diagnose breast cancer reliably and efficiently. This paper reports an approach to the detection of one marker, circumscribed masses, using a combination of detection criteria used by experts. The cirteria include the shape, brightness contrast and uniform density of tumor areas. Our techniques employ modified median filtering to enhance mammogram images and template matching to detect breast tumor. The results obtained by applying these techniques to 24 test images are described.

KEYWORDS : breast tumor, mammogram, median filter, template matching, cross-correlation.

1. Introduction

Breast cancer is a leading cause of death among all cancers for women of middle age and older [14]. Although no prevention exists at this time, early detection and subsequent surgery is expected to result in lower death rates. Mammography has been found to be an effective breast screening technique and mass screening of mammogram is being considered as a potential approach to detect breast cancers at the earliest possible stage [17]. A major problem in such a screening program is that it involves the interpretation of the large volume of mammograms by expert radiologists. Due to the shortage of radiologist and the need to improve the cost benefit ratio of such a program, the need to construct computer-aided systems to diagnose breast cancer in mammogram becomes apparent.

In diagnosing breast cancer, radiologists use several indicators or "markers" in mammograms, all being defined by a set of criteria, such as area, brightness contrast and shape. Our long-term goal is to implement an expert system for breast cancer diagnosis based on the same set of markers and criteria the experts use. At a first stage, we are concerned with the reliable detection of likely tumor sites. Our major obstacle in this approach is the fact that experts' verbal descriptions of markers cannot be easily translated into a set of image analysis procedures. This paper is concerned with our approach to the detection of one marker, *circumscribed masses*, using a combination of detection criteria considered relevant by experts.

The evaluation of mammograms by computer can be roughly divided into three sequential processes [5] :

1. location of suspicious areas within the breast image,
2. extraction of local descriptive features from suspicious areas,
3. feature-based classification of these areas (into non-tumors, benign or malignant tumor areas).

In the past, several groups [1,16], have demonstrated the potential use of computers in feature extraction and classification of suspicious areas. Since human assistance is needed to locate these areas before the computer processes the images, these systems are not fully automated. If automatic screening of mammogram is to become a practical reality, it is necessary to develop algorithms that reliably detect suspicious tumor areas in mammograms.

Many computer-aided techniques have been developed for the analysis of medical images, but their effectiveness is very often application dependent. This is analogous to the fact that radiologists adopt different strategies to analyse different types of medical images. In addition, different imaging processes produce images with different characteristics which in turn affect the effectiveness of a given image processing technique. For instance, in the detection of Pneumonconiosis Opacities in chest X-Ray [11], the well defined equal-density contours within opacities provide a firm support for the logic upon which *Li, Savol and Fong*'s region growing algorithm is based. Therefore, it is obvious that the choice of technique used in locating suspicious areas in mammograms is directly related to the criteria used by experts and to the characteristics of mammogram images.

In the case of circumscribed masses, the criterion used by radiologist for distinguishing *"suspicious"* from *"clearly normal"* regions on a film mammogram is that a suspicious area is a bright (comparing with surrounding tissues) and approximately circular area of uniform density, and of varying size [15]. Inspite of these characteristics, locating suspicious areas in mammograms is difficult for a number of reasons. The small differences in density between normal and tumorous tissues in human breast create little contrast between a tumor area and its background in the image. This contrast is also reduced in the filming and digitization process of the mammogram images. In addition, the presence of noise and other anatomical structures, such as ducts and glands increases the background variations of tumor areas. The boundaries of tumor areas are fuzzy and in some instances, boundaries may be only partially visible. Together with the small size of early-stage

tumors, they defeat any attempt to segment the image by global gray level thresholding technique. Also, they make some tumor areas lose some of the well-defined characteristics mentioned above. To tackle these difficulties, a modified median filter was designed to increase the brightness homogeneity of both tumor and non-tumor areas in the image while preserving edges of tumor sites. Then a template-matching method with a relaxed target picking criterion is used to locate suspicious tumor areas in the filtered image.

2. Image Enhancement

There are two possible approaches to enhance mammographic features. One is to increase the contrast of suspicious areas and the other is to reduce their background variations. Some techniques for contrast enhancement of film mammograms have been suggested earlier [4,7]. Their method is based on adaptive neighbourhood processing with a set of contrast enhancement functions or an optimal one to enhance the contrast of mammographic features. In our research, we take the other approach and enhance the images by reducing the background variations while preserving the contrast of suspicious areas in the images.

2.1 Median Filtering

Conventional low-pass filtering techniques are inappropriate for enhancing mammograms, because they tend to blur the image and cause further loss of the fuzzy tumor edges. It is suggested in [9] that a non-linear filter, the median filter, is particularly suitable for enhancing medical images due to its ability to provide both noise reduction and edge preservation.

The two-dimensional median filter is defined as follows :

For a window W(i,j) centered at image coordinates (i,j) the median filtering output is

$$\hat{P}_{ij} = \text{median} \{ P_{i'j'} : (i', j') \in W(i,j) \}$$

where P_{ij} is the gray level of the pixel at image coordinate (i,j). (See [13], vol 1, p. 261-264)

By considering the diversity of information in an image and the features we want to select, enhance, suppress or uncover, it is believed [9] that non-linear filtering techniques are sometimes advantageous over linear techniques because they are versatile and adaptable to local conditions of noise level and object structure. Some theoretical background about median filters can be found in [3,6].

2.2 Selective Median Filtering

Experimental results showed that the edge preservation power of a pure median filter is not sufficient enough for enhancing mammogram images due to the fuzziness of the tumor boundaries. In order to further preserve the tumor boundaries, a modification of the median filter is introduced and is termed as Selective Median Filter (SMF). The two-dimensional Selective Median Filter is defined as follows :

For a window W(i,j) centered at image coordinates (i,j), the selective median filtering output is

$$\hat{P}_{ij} = \text{median} \{ P_{i'j'} : (i', j') \in W(i,j) \text{ and } | P_{i'j'} - P_{ij} | < T \}$$

where T is a threshold and P_{ij} is the gray level of pixel at image coordinate (i,j).

Thus, in computing the median, the set of pixels is restricted to those with a difference in gray level no greater than T. By adjusting T, the amount of edge smearing can be controlled. This modification of the median filter is related to selective averaging schemes developed for linear filters [13] that have shown good results in improving the edge preserving power of linear low-pass filters.

In general, to achieve sufficient noise suppression, one needs either a filtering technique allowing a large window size, or the filter has to be applied repeatedly to the data [10]. Median filters act as low-pass filters in homogeneous areas and as their window size increases, they respond with increasingly narrow pass-bands [6]. *Huang* has shown that as the window size increases, noise is reduced but distortion is introduced into the actual signal [3]. Therefore in using the SMF, we are forced to iterate the filtering operation to achieve sufficient noise reduction.

The pure median filter has no design parameters other than the window size and cannot be adjusted to the given signal and noise characteristics. Such filtering may degrade important information in some type of images or possibly introduce artifacts [9]. The selective median filter, SMF, has three design parameters that can be varied to adjust the filter to the noise characteristics of all mammogram images. The parameters are the window size W, the gray level difference threshold T and the number of iterations. The effect of the SMF is mainly controlled by the threshold T. If T is large, the edge preserving power of SMF is strong, but its smoothing effect will be small. If T is small, the SMF behaves the other way round.

2.3 Experimental Results

To evaluate our approach, a test set of 24 mammogram films was used. The suspicious area(s) on each film was marked according to the diagnosis of expert radiologists. Images of the 24 film mammograms were digitized by a video camera into a square array of 512x512 pixels with 256 possible gray levels at each pixel. To save processing time, each 512x512 array was further reduced to a 256x256 array by a neighbourhood-averaging method with a window size of 3x3 pixels. All images, except one, contained circumscribed masses. But in evaluating the SMF performance, other sites which were classified as "suspicious" by the experts were included as objects to be detected.

To estimate the maximum value for parameter T, the contrast between pixels in many tumor areas was checked. It was noted that the maximum contrast was around 15. However, as the contrast between some suspicious areas and their background is very small, a smaller threshold value was used to preserve edges of all suspicious areas. Best performance of the SMF was found for window size W = 9x9, number of iteration = 5 and edge threshold T = 5.

With selective median filtering, background variation is reduced in the filtered images while the boundaries of all suspicious areas are preserved. To see the effect of the SMF, a high-pass filter (Laplacian) was applied to the filtered images and the result for the best case (with a prominent tumor area) and the worst case (with a tumor area which is difficult to detect even by radiologists) are shown in Figures 5 and 6. In Figure 5, the boundary of the tumor area appears as a closed ring and the rest of the image is quite clear. But in Figure 6, the boundary of the tumor area appears as a broken ring and there is a lot of noise both inside and outside the tumor area. The original images are shown in Figures 1 and 2 and the SM-filtered images are shown in Figures 3 and 4.

The performance of SMF does not improve much after the 5th iteration if the other two parameters (W and T) are kept constant. This is in agreement with *Gallarger* and *Wise*'s observation that every signal can only be reduced down to a certain point no matter how many times we apply the median filter [4]. This suggested the concept of a filtered passband and stopband. At its stopband the filter is invariant to subsequent filtering.

3. Locating Tumor Areas

By examining the criteria used by radiologist to extract suspicious areas from film mammograms, we notice that the approximately circular shape and the brightness homogeneity of tumor areas are important characteristics used in detecting suspicious areas. (Note that edge fuzziness is an additional indicator of circumscribed masses, but it is not used in our present work yet.) Among the techniques developed for object detection, two approaches which make use of the shape characteristic of the target object are being considered. One is to use the region information by applying algorithms to search for a homogeneously-dense region with circular shape. The other approach is to use the boundary information on a high-pass filtered image and to detect ring like structures. The result reported in this paper is based on the first approach.

To find regions of uniform density and approximately circular shape, we use a template matching technique. Template matching is a classical approach to object detection. To locate an object, an image or a search area is searched for the object represented by a small image "window" or "template". In the case of tumor detection, the search area is a SM-filtered mammogram image and the template is an integer array which represents an 'ideal' tumor.

The template used to match tumors with a diameter of 5 pixels is shown in Figure 7. The templates are designed so as to ascribe varying weights to points within the templates. The circular patch of 1's in the centre of the template represents a tumor area having uniform density. To allow tumor shape to deviate slightly from a perfect circle, the patch of 1's is bounded by a ring of 0's. This is a "don't care" area in the match. The background of the patch is filled with -1's instead of 0's, because we are looking for a light object on a dark background. The size of the ring of 0's and the background in each template increase in proportion to the size of tumor the template represents. In addition, the shape of the template is circular instead of squared, so as to increase the sensitivity of the match. By using a circular template, all the neighboring pixels which locate evenly around the tumor are checked in the matching process.

The measure most widely used for the similarity measure between two subimages is cross-correlation. Let S be the filtered image, an LxL array of pixels each taking one of K gray levels; W be the template, which is MxM with $M < L$. Each MxM subimage of S can be uniquely referenced by its upper left corner coordinates (i,j). There are $(L-M+1)(L-M+1)$ such (i,j)'s.

The unnormalized cross-correlation between image and template is defined as

$$R(i,j) = \sum_{k=1}^{M} \sum_{m=1}^{M} W(k,m)\, S(i+k-1, j+m-1)$$

and tumor locations can be defined as peaks of R(i,j) over the whole image area.

One disadvantage of using unnormalized cross-correlation is that it is sensitive to properties of the image that may vary with the offset, such as its average brightness. As a result, the maximum of the unnormalized correlation does not always yield the real location with the exact match [2]. Improved detection performance is achieved by using normalized cross-correlation, which is defined as [13] :

$$R_n(i,j) = \frac{\sum\sum (W - \mu_w)\ \sum\sum (S - \mu_s)}{\sqrt{\sum\sum (W - \mu_w)^2\ \sum\sum (S - \mu_s)^2}}$$

where n is the radius of the circle in a template, μ_W is the mean of the template and μ_S is the mean of subimage.

This normalized cross-correlation is designed to handle both a constant gain and a constant offset. To illustrate this, suppose the pixel intensities from the subimage are equal to a constant factor (gain) times the intensities from the template, plus a constant offset. Let the gain be **a** and the offset be **b**. Subtracting the means removes the problem of the offset; dividing by the variance takes care of the gain. As a result its absolute value equals one if and only if $W(i,j) = \mathbf{a}*S(i,j) + \mathbf{b}$. This can lead to multiple match candidates if several areas of different relative gains and offsets resemble each other. However, this merely introduces false alarms, but does not discard true suspicious areas.

One disadvantage of using correlation as the similarity measure is that the orientation and size of the target object may disturb the match [12]. However, the shape of the tumor area is circular, therefore, the match is orientation invariant. To cope with size variations of the object, twelve templates with different sizes are used to match against each of the 24 images. The circle in the smallest template has a radius of two pixels, where as that of the largest template has a radius of fourteen pixels.

Due to the design of the templates, a circular dark object on a bright background will produce a large negative cross-correlation value. Hence, locations in the images which have negative cross-correlation values are not considered as suspicious areas.

To pick suspicious areas, the following criteria are considered:

1. pick the location with the maximum cross-correlation value,
2. pick the locations with the maximum cross-correlation value

for each of the twelve templates used,

3. pick all the locations with cross-correlation value exceeding a threshold.

Although most suspicous areas have the maximum cross-correlation value when being matched with one of the twelve templates, it is not possible to use the first two criteria in this application. This is due to the fact that a mammogram film may contain more than one suspicious area, and several suspicious areas in the same mammogram film may have the same size. Hence, a more relaxed criterion must be used. The third criterion requires a threshold to be found for each image film. A single threshold for all images is not sufficient, because of the following reason. It is observed that the breast image in some mammograms, such as the one shown in Figure 2, contain a lot of glands and fatty tissues which produce a very rich texture in the images. As a result, these images create many false suspicious areas that have large cross-correlation values. Some of these values are even greater than those of the suspicious areas in other images. Therefore, a single threshold will either produce too many false alarms or miss some true suspicious areas.

A "percentile" method [5] is used to determine a threshold for each image. We assume that suspicious areas only occupy a fixed percentage of the breast area. Hence, by analysing the normalized cross-correlation distribution of an image, we choose a threshold value, **R**, such that **q** percent of the locations in the image having a correlation larger than **R** are considered as suspicious areas. This corresponds to mapping **q** percent of the locations into suspicious areas and the value of **q** is constant for all images.

To implement this scheme, for each image, the largest among the twelve cross-correlation values (corresponding to the twelve templates) computed for each image coordinate was stored in a two-dimensional array. To save processing time, locations which had a cross-correlation value less than 0.2 were discarded as insignificant locations. Then the centre of each 'significant' locations in the array was determined based on the given radius and cross-correlation value. Among these locations, **q** percent, having the largest cross-correlation value were picked as suspicious areas in each image.

The cross-correlation distribution curves built for the images shown in Figure 3 and 4 are displayed in Figure 8 and 9 respectively. The mean cross-correlation value among the 24 images is around 0.35 and the largest value is 0.8. Investigations showed that to produce a zero miss rate, the minimum **q** value was 2.5 . Using such a **q** value, seven suspicious areas were reported, on average, in each of the 24 images.

4. Discussion

The result we have obtained with our approach is quite encouraging. By combining three criteria, namely the contrast, the uniform density and the circular shape of tumor areas, the detection algorithm is capable of locating all the tumor areas. Nevertheless, work is in progress to further improve the tumor detection algorithm and further testing on a large number of samples will be conducted.

To remove false alarms produced by the template matching method, tests are designed to discriminate between these false alarms and true suspicious areas. It is observed, for example, that many of the false alarms are caused by the presence of noise and anatomical structures in the image and their contrast is very small when compared with that of the true suspicious areas. To discriminate these false alarms, a gray level histogram is constructed in each suspicious site using the known tumor radius. Locations which have a single-peaked histogram are rejected as possible suspicious areas. This method relies heavily on the structure of the gray level histogram, which contains peaks and valleys corresponding to gray level subpopulations of the image. A tumor and its surrounding area (represented by histogram peaks) are assumed to differ in average gray level. Hence, a true suspicious area must have at least two peaks in its gray level histogram. Applying this test to the output of the template matching process, about half of the false alarms can be rejected.

The computational cost of our template matching method is very high. Some efforts are presently devoted to find ways to speed up the computation at each test location in a mammogram image. One way to speed up the computation is to use the Fast Fourier Transform algorithm. However, the cost in normalizing the images before applying the transformation may dwarf the benefit in computing the correlation in the frequency domain. But the feasibility of this method still awaits further investigation.

In addition to improving the present techniques, we are extending the techniques developed for detection of circumscribed mass to the detection of other markers. Even though the criteria in detecting circumscribed mass and other markers are closely related, we expect the need to incorporate additional criteria for detecting other markers reliably.

References

1. L.V. Ackerman and E. Gose, "Breast Lession Classification by Computer and Xeroradiograph," *Cancer,* 30, pp. 1025-1035, 1972.
2. D.I. Barnea and H.E. Silverman, "A Class of Algorithm for Fast Digital Image Registration," *IEEE Trans. Comput.,* C-21, pp. 179-186, Febuary 1972.
3. A.C. Bovik, T.S. Huang and D.C. Munson, "The Effect of Median Filtering on Edge Estimation and Detection," *IEEE Trans. Pattern Anal. and Machine Intell.,* PAMI-9, No. 2, pp. 181-194, March 1987.
4. A.P. Dhawan, G. Buelloni and R. Gordon, "Enhancement of Mammographic Features by Optimal Adaptive Neighborhood Image Processing," *IEEE Transactions on Medical Imaging,* MI-5, No. 1, pp. 108-120, March 1986.
5. W. Doyle, "Operation Useful for Similarity-Invariant Pattern Recognition," *J. Assoc. Comput. Mach.,* 9, pp. 259-267, 1962.
6. N.C. Gallaager and G.L. Wise, "A Theoretical Analysis of the Properties of Median Filters," *IEEE Transaction On Acoustic, Speech Signal Processing,* ASSP-29, No. 6, pp. 1136-1141, December 1981.
7. R. Gordon and R.M. Ranagayyan, "Feature Enhancement of Film Mammograms Using Fixed and Adaptive Neighborhoods," *Appl. Opt,* 23, No. 4, pp. 560-564, 1984.

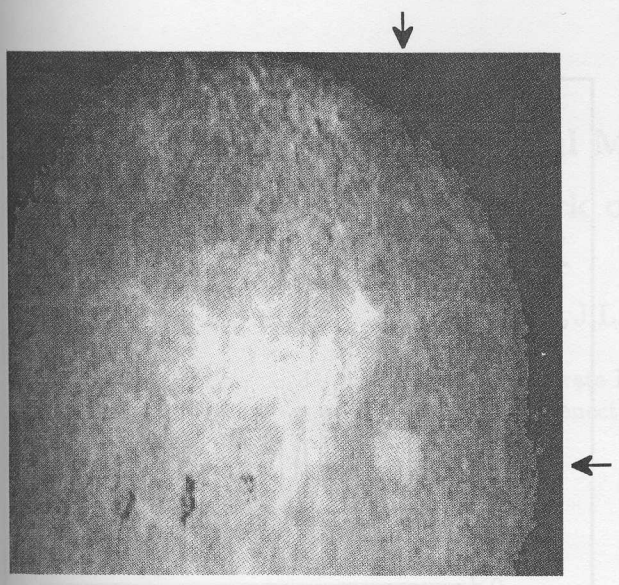

Figure 1. Mammogram with easily detectable circumscribed mass at position indicated by markers on edge of the Figure.

Figure 3. Selective Median filtered version of Figure 1.

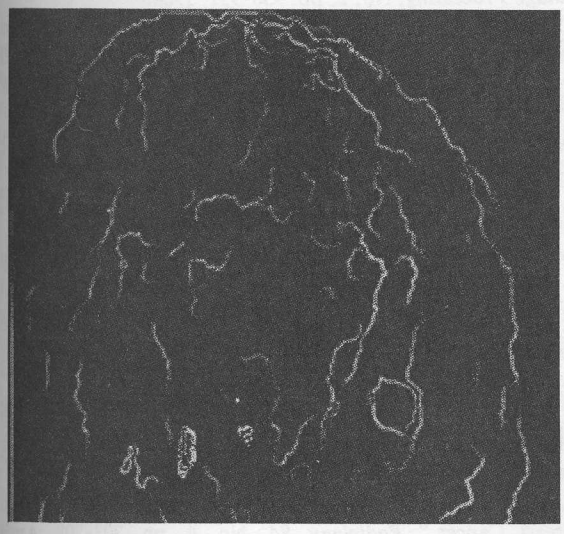

Figure 5. Laplacian of Figure 3 showing tumor boundary as a closed ring.

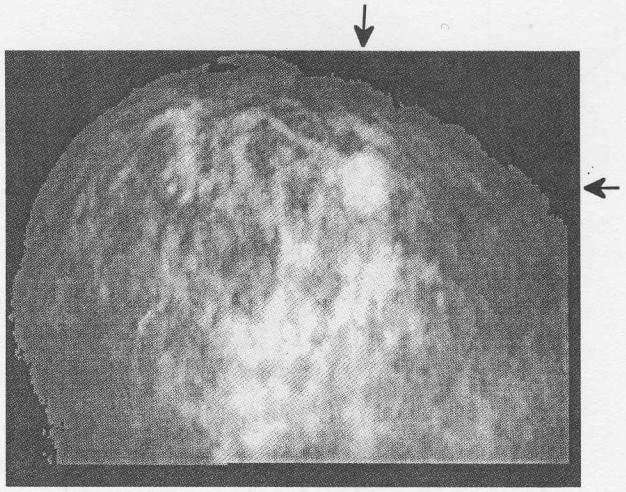

Figure 2. Mammogram with circumbscribed mass that is difficult to detect. Its position is indicated by markers on edge of the Figure.

Figure 4. Selective Median filtered version of Figure 2.

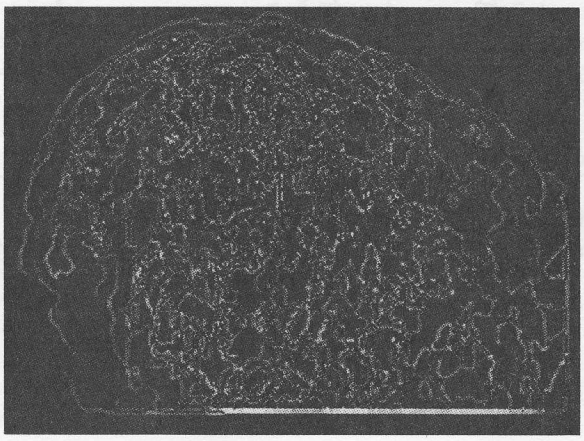

Figure 6. Laplacian of Figure 4 showing partial tumor boundary and many "false alarm" edges.

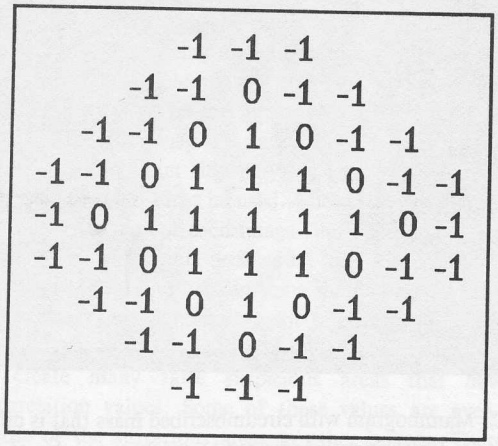

Figure 7. A template with a circle of diameter 5

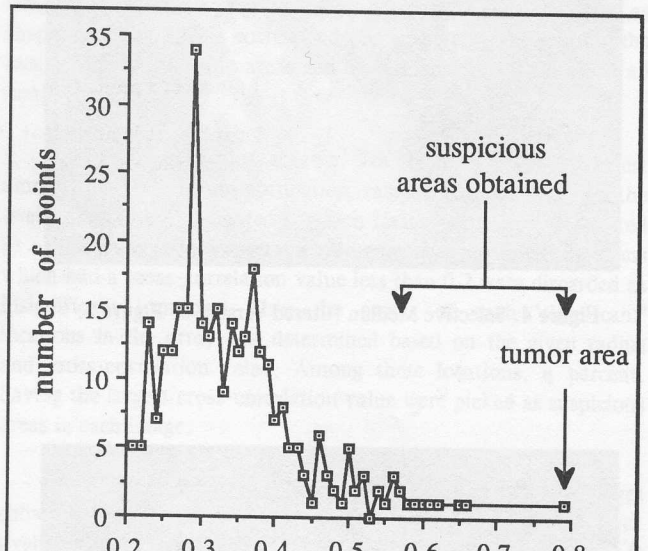

Figure 8. A distribution curve of normalized cross-correlation values computed for the image in Figure 3. Using a **q** value of 2.5, the threshold, **R**, of this image is 0.58.

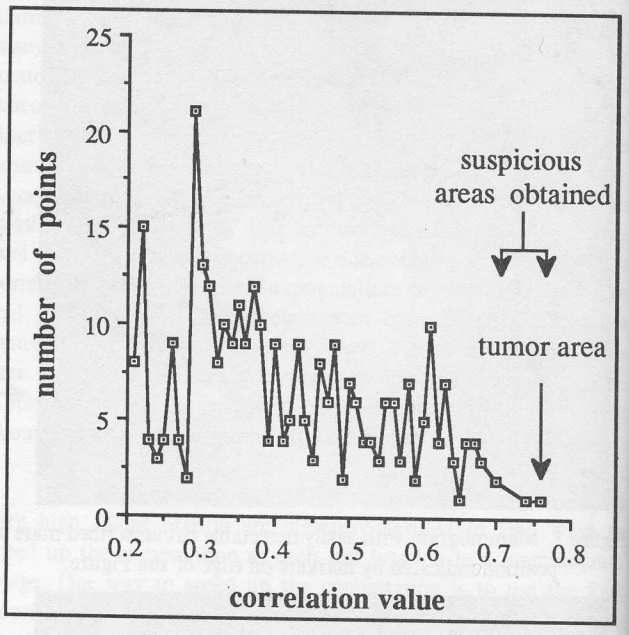

Figure 9. A distribution curve of normalized cross-correlation values computed for the image in Figure 4. Using a **q** value of 2.5, the threshold, **R**, of this image is 0.67.

References (continued)

8. W. Hand, J.L. Semmlow, L.V. Ackerman and F.S. Alcorn, "Computer Screening of Xeromammograms : A Technique for Defining Suspicious Areas of the Breast, " *Computers & Biomed. Research,* 12, pp. 445-460, 1979.
9. A. Ioannidis, D. Kazakos and D.D. Watson, "Application of Median Filtering on Nuclear Medicine Scintigram Images," *IEEE Trans. Pattern Reg. and Image Proc.*, No. 1, pp. 33-36, 1984.
10. Y.H. Lee and S.A. Kassam, "Application of Non–linear Filter for Image Enhancement," *IEEE Trans. Patterns Reg. and Image Processing,* No. 2, pp. 930-931, 1984.
11. C.C. Li, A.M. Savol and C.P. Fong, "An Improved Algorithm for the Dectection of Small, Rounded Pneumonconiosis Opacities in Chest X–Rays," *IEEE Transaction on Medical Imaging*, pp. 370-395, 1978.
12. W.K. Pratt, *Digital Image Processing,* New York : Springer-Verlag, 1981.
13. A. Rosenfeld and A.C. Kak, *Digital Picture Processing,* Vol. 1 and 2, 2nd edition, New York : Academic, 1982.
14. F. Siverberg and A.L. Holleb, "Cancer Statistics," *C. Cancer J. Clin.*, 21, pp. 13-31, 1971.
15. L. Tabar and P.B. Dean, "Basic Principles on Mammographic Diagnosis," *Diagnostic Imaging and Clinical Medicine,* 54, pp. 146-157, 1985.
16. F. Winsberg, "Detection of Radiographic Abnormalities in Mammograms by means of Optical Scanning and Computer analysis," *Radiology,* 89, pp. 211-215, 1967.
17. J. N. Wolfe, "Mammography as a Screening Examination in Breast Cancer," *Radiology,* 84, No. 4, pp. 703-708, April 1965.