Abstract—Diagnostic features in mammograms vary widely in size and shape. Classical image enhancement techniques cannot adapt to the varying characteristics of such features. An adaptive method for enhancing the contrast of mammographic features of varying size and shape is presented in this paper. The method uses each pixel in the image as a seed to grow a region. The extent and shape of the region adapt to local image gray-level variations, corresponding to an image feature. The contrast of each region is calculated with respect to its individual background. Contrast is then enhanced by applying an empirical transformation based on each region's seed pixel value, its contrast, and its background.

A quantitative measure of image contrast improvement is also defined based on a histogram of region contrast and used for comparison of results. Using mammogram images digitized at high resolution (less than 0.1 mm pixel size), it is shown that the visibility of microcalcification clusters and anatomic details is considerably improved in the processed images.

I. INTRODUCTION

R ECENT studies show that one in 10 Canadian women will contract breast cancer in their lifetime, and that breast cancer is the leading cause of death of women between the ages of 35 and 54 [1]. Early detection is the most successful method of dealing with this epidemic. Currently, the best method for early detection is the use of mammography. Other techniques, such as computed tomography, magnetic resonance imaging, ultrasound, and transillumination have been investigated [2], [3], but mammography remains the proven technique. Studies have shown a decrease in both severe breast cancer and mortality in women who undergo regular mammographic screening, due to earlier detection and treatment [4], [5]. However, periodic screening programs present the examining radiologist with an increased caseload, increasing the chances of improper diagnosis. In addition, mammograms are among the most difficult of radiological images to interpret. Mammograms are of low contrast, and features in mammograms indicative of breast disease are often very small. Digital enhancement of mammograms allows a more confident interpretation of difficult cases without resorting to follow-up patient examinations and secondary procedures, as well as allowing quicker diagnoses of routine cases. Also, the large numbers of negative biopsies encountered in current practice [6] can be reduced if an enhanced mammogram provides a more certain diagnosis. If digital images are available, the potential for computer-aided analysis of mammograms also arises. With the advent of high-resolution image digitization hardware, the decreasing cost/performance ratio of computers, and the recent development of digital X-ray image acquisition equipment, computer image enhancement is becoming practical for mammograms.

Conventional image processing techniques do not perform well on mammographic images. The large variation in feature size and shape reduces the effectiveness of classical fixed-neighborhood techniques, such as unsharp masking. This paper presents a technique which adapts to image features, and enhances these features with respect to their surroundings, regardless of the feature shape and size [7]–[11]. We call this technique “region-based image processing” [12].

II. ENHANCEMENT AND ANALYSIS OF MAMMOGRAMS

The fundamental enhancement needed in mammography is an increase in contrast, especially for dense breasts. Contrast between malignant tissue and normal dense tissue may be present on a mammogram, but below the threshold of human perception. As well, calculations in a sufficiently dense mass may not be readily visible because of low contrast, so that defining the characteristics of calcifications is difficult.

Little work has been reported to this point on enhancing mammograms. Photographic unsharp masking [13], digital unsharp masking [14], and spatial bandpass filtering [15] have been used to enhance mammograms. More work has been done on analysis of mammograms, for identification of image features associated with cancer. Automated detection of tumors or lesions has been investigated [16]–[20], although few studies [17] have tested their methods on large numbers of cases. Detection of calcifications has also received considerable attention [15], [21]–[25], with near-acceptable results being reported. Pattern recognition techniques [26], [27] and expert systems [28] have been developed to classify predefined anomalies, with generally good results for the limited test cases presented. Clearly, the emphasis in mammogram imaging research has been in pattern recognition for diagnostic purposes using, at best, rudimentary enhancement of the images. With few exceptions [15], [18], images have been acquired at spatial resolutions insufficient to resolve the necessary fine detail in mammograms. The approach taken in this paper is to enhance difficult mammograms to sufficient
quality to allow the radiologist to make his diagnosis with more confidence. We employ high-resolution digitization (less than 0.1 mm square pixel size), and maintain high resolution throughout our processing procedures. Further, information is obtained during enhancement which can provide a preliminary quantitative analysis of mammographic features. Our emphasis at this stage is to provide the radiologist with a superior image, not a diagnosis. Further analysis of image features using shape analysis techniques will be taken up later.

### III. IMAGE CONTRAST

In practice, many definitions of contrast are used [29]. In general terms, contrast refers to the difference in luminance between an object and its surroundings. In psychovisual studies, the contrast $C$ of an object with luminance $f$ against its surroundings of luminance $b$ is defined as follows:

$$ C = \frac{f - b}{b}. $$

The optical definition of contrast is

$$ C = \frac{f - b}{f + b} $$

where $f$ is the maximum luminance in the image and $b$ is the minimum luminance. This definition of contrast has the advantage of being bounded between $+1$ and $-1$.

Consider an object that is just noticeably distinct from a uniform background. If we define the luminance difference between the central area and the overall image luminance as $\Delta L$ and the overall image luminance as $L$, the ratio between the two is called the Weber ratio $W$

$$ W = \frac{\Delta L}{L}. $$

The Weber ratio varies strongly with the size and shape of the foreground and the background of an object. However, for simple objects over a brightness range from 1 ft Lambert to 1000 ft Lambert, $W$ may be considered to be approximately 0.02 [30]. A region which differs in luminance from its surroundings by less than 2% is indistinguishable to the human eye. The aim of contrast enhancement schemes is to increase image contrast over this threshold.

This paper will use a version of (2) as the definition of contrast. We deal with gray-level images, and define $f$ as the mean gray-level value of a particular object in the image, called the foreground, and $b$ as the mean gray-level value of a surrounding region called the background. Then, contrast $C$ is defined in (2). This definition of contrast is independent of the actual range of gray levels in the image, and so is well suited to contrast transformation schemes. If we compare (2) with the Weber ratio in (3), we see that we are assuming that the object and its background have equal area and thus we are equating $(f + b)/2$ to $L$, the total image luminance, and $(f - b) = (f - b)/2$ to $\Delta L$, the luminance difference. For the human eye then, we need to increase $C$ above 2% or 0.02.

### IV. CONTRAST ENHANCEMENT TECHNIQUES

#### A. Enhancement by Contrast Stretching

The simplest method of increasing the contrast in an image is to adjust the image histogram so that there is a greater separation between foreground and background gray level distributions. A simple example of contrast stretching is a linear rescaling of the gray level distribution in the image. Denoting the input image gray scale values by $x$, and the output gray scale values by $y$, the rescaling transformation is

$$ y = kx + m $$

where $k$ and $m$ are nonzero. Depending on the specific values of $k$ and $m$, contrast will be increased or decreased. Alternatively, a nonlinear transformation can be used, such as

$$ y = kx^p $$

where $k$ is a factor to rescale the output image to the range of the input image, depending on the value of $p$. In either case, compression (and possibly removal) of one section of the image gray level histogram is necessary to allow expansion in another section, if the original gray level range is to be maintained. This technique usually requires that an optimal transformation be specified for each given image.

#### B. Enhancement by Histogram Equalization and Specification

If we consider the image histogram as a probability distribution, then from an information theoretic stand-point, the distribution which conveys the most information is a uniform distribution [31]. Therefore, if we redistribute the gray levels to obtain as uniform a histogram as possible, the image information should be maximized, since we are using the available intensity range "optimally." It can be shown [30] that histogram equalization can be effected by replacing each normalized gray level with the cumulative distribution from the minimum gray level up to that gray level.

Locally adaptive histogram equalization performs histogram equalization independently over different segments of the image. Ideally, a histogram is generated in a window centered on each pixel in the image, equalized, and used to calculate a new value for that pixel. This procedure is computationally very intensive, so techniques have been developed to interpolate between a few such histograms equally spaced through the image to obtain the equalized image [32]. Adaptive histogram equalization has been shown to enhance contrast in radiological images, which in general have a large global dynamic range, but small local feature gray-level variations [33]. The area of the image immediately surrounding a given pixel is used to calculate a histogram, which is then equalized to give the new pixel value. The optimal size of the histogram area is difficult to determine, and often varies from one area of the image to another. The often radically different appearance of the image after the equalization may be undesirable in some classes of images, including mammograms.

A variation on histogram equalization is histogram specification. An empirically derived histogram transformation can
be applied, with very good results in many cases [30]. The disadvantage of histogram specification is that the transformation must be designed for each image individually.

C. Fixed-Neighborhood Statistical Enhancement

In many classes of images, a slowly varying background contributes little to the interpretation of the image, and can be removed to allow expansion of the gray level variations in local image features, and thus increase contrast. Local enhancement techniques use statistical properties in the neighborhood of a pixel to estimate the background, suppress it, and increase local contrast. Lee [34] calculates the local mean and variance, and performs a transformation to a desired local mean and variance. Narendra and Fitch [35] use the global mean, local mean, and local standard deviation to obtain the gray level transformation:

\[ y = \frac{M}{\sigma}(x - \mu) + \mu \]  

where \( \mu \) and \( \sigma \) are the local mean and standard deviation, \( M \) is the global mean, and \( k \) is an empirically determined scaling factor. As in the methods discussed above, determination of the local neighborhood dimensions is the critical step. A given neighborhood size and shape may not be equally effective in enhancing all areas of an image.

D. Convolution Mask Enhancement

Convolutional masking is one of the most commonly used methods of digital image enhancement. Unsharp masking is an enhancement operation which was originally performed photographically. In this method, a blurred photographic negative is placed in register with a positive image to obtain a difference image containing the details in the image. This "details only image" is then amplified and added to the blurred positive image and a print is obtained. The resulting print is sharper because low-frequency information in the image is reduced in intensity while high-frequency details are amplified. Digital unsharp masking approximates this process using a \( 3 \times 3 \) mask. An example of such a \( 3 \times 3 \) unsharp mask \( H(i,j) \) is

\[ H(i,j) = \begin{pmatrix} -1/8 & -1/8 & -1/8 \\ -1/8 & 2 & -1/8 \\ -1/8 & -1/8 & -1/8 \end{pmatrix}. \]  

Rogowska et al. [36] and Sezan et al. [37] have applied digital unsharp masking to digital chest radiographs. Daponte and Fox [38] have used Sobel gradient operators to enhance chest radiographs. These procedures change the appearance of the image too radically to be applicable in mammograms, where the overall subjective appearance of the image is essential for diagnosis.

E. Enhancement by Background Removal

A direct method of reducing the slowly varying portions of an image, to allow increased gray level variation in image details, is background subtraction. It is usually performed by subtracting a low-pass filtered version of the image from itself. Unsharp masking is a simple version of this procedure. Spline filtering [39] and gray-scale morphological processing [40] are two methods of estimating the image background which have been used successfully for this purpose. The background extraction technique should be adaptive to local image characteristics to truly identify the image background.

F. Region-based Enhancement

The above techniques can all be classified as either fixed-neighborhood or global techniques. They may adapt to local features within a neighborhood, but do not adapt the size of the neighborhood to local properties. Alternatively, they modify the image depending on global properties, such as the image spatial-frequency spectrum, which may not be representative of a small region of interest in the image. Many images, including mammograms, have isolated regions which are the primary features of interest. These features can vary widely in size and shape, and often cannot be enhanced by fixed-neighborhood or global techniques. Thus there is a need for adaptive-neighborhood techniques [7]–[11], [41]–[45]. We have developed adaptive-neighborhood processing techniques which grow regions in a given image and enhance the regions with respect to their local backgrounds.

V. REGION-BASED IMAGE PROCESSING

In adaptive-neighborhood or region-based image processing, a neighborhood is defined about each pixel in the image, the extent of which is dependent on the characteristics of the image feature in which the given pixel is situated. This neighborhood of similar pixels is called a region. In image segmentation, groups of pixels are found that have some property in common (such as similar gray level) and are used to define disjoint image regions called segments. Region-based processing may be performed by initially segmenting the given image and then processing each segment in turn. Alternatively, region-based processing may define possibly overlapping regions for each pixel and process each of these regions independently. Regions, if properly defined, should correspond to image features. Then, features in the image are processed as units, rather than pixels being processed using arbitrary groups of neighboring pixels (for example, \( 3 \times 3 \) masks). Image processing procedures can then be applied on an image feature basis, rather than pixel by pixel. Region-based processing could also be designated as pixel-independent processing, feature-based processing, adaptive neighborhood processing, or object-oriented processing. The term adaptive region-based image processing, or simply region-based processing is used in this paper.

The fundamental step in a region-based image processing algorithm is defining the extent of regions in the image. Again, we emphasize that there are two classes of regions: nonoverlapping regions, which are obtained using image segmentation techniques; and overlapping regions, obtained from region growing techniques. Overlapping regions are used here, because it is felt that disjoint segmentation of an image, with subsequent enhancement of the segments, would result in noticeable edge artifacts and an inferior enhanced image.
VI. REGION GROWING

A. Seed-Fill Region Growing

The region growing technique used in this paper is based on a simple graphical seed-fill algorithm. It is also known as pixel aggregation [30]. In this method, regions consist of connected pixels that fall within a specified gray-level deviation from the starting or seed pixel. For the high-resolution mammogram images studied in this work, 4-connectedness was found, by visual comparison, to be usually adequate to allow accurate region growing, although small features were better matched with 8-connected regions. Longer processing times result for 8-connectedness, which was used unless processing became onerous.

The flowchart of Fig. 1 shows the region growing algorithm. The algorithm starts with a given pixel, called the seed pixel, or simply seed. This pixel is placed in an initially empty queue, which holds pixels to be evaluated for inclusion or exclusion from the region being grown. The main loop is then entered. If the queue is empty, the program exits the loop. Otherwise, the first pixel is taken from the queue. This pixel is called the current pixel. If its gray level value is within the specified deviation form the seed, it is labeled as a foreground pixel. Its immediate neighbors (either 4-connected or 8-connected, as specified) are possibly foreground pixels, and are added to the queue, if they are not already in the queue from being connected to previously checked pixels. If the current pixel is outside the allowable gray level range, it is marked as a background pixel, and a border pixel of the region has been reached. Regions can have a number of internal borders, in addition to the encompassing external border. Thus, the background may consist of more than one set of pixels, with each such set being disconnected from the others. After all of the current pixel’s neighbors have been checked, control is directed back to the start of the loop, to check the next pixel in the queue. The final step in finding a region about the seed is completing the background. This is done by starting with the existing background points, as found during foreground growth. The neighbors of this set of pixels are examined to see if they belong to either the foreground or background. If not, they are set to be the next layer of the background. The new layer is then used to grow...
another layer, and so on, until the specified background width is achieved. The region-growing procedure as described above does have inefficiencies, in that a given pixel may be checked more than once for placement in the queue. More complicated algorithms can be used to grow regions along line segments, and thereby partially eliminate this inefficiency [46]-[48]. Preliminary testing of a scan-line based algorithm showed minimal improvement for mammogram images, as the type of regions grown in mammograms are usually complex. Fig. 2 shows region growing graphically. Note that each pixel in the connected foreground that has the same gray level as the seed will grow the same foreground and background. These pixels are called the region’s redundant seed pixels. Considerable computation can be saved by using this redundancy and obviating the repeated growing of the same region. Further, the same final transformation that is applied to the region’s seed pixel is also applied to the region’s redundant seed pixels. In high-resolution mammogram images, redundant seed pixels were seen to account for over 75% of the image pixels. This large percentage is partially due to the dark background in the image off the projection of the breast. Also, the redundant pixel percentage is dependent on the growth tolerance used during region growing. In images with large, uniform regions, the percentage of redundant seed pixels could be even higher.

B. Region Growing Parameters

The crucial parameter in controlling seed-fill region growing is the criterion used to decide whether a pixel is to be included in the region foreground or excluded. This criterion is defined as the growth tolerance, \( \gamma \). The growth tolerance indicates the deviation (positive or negative) about the seed pixel’s gray level that is allowed within the foreground region. For example, with a growth tolerance of 0.05, any pixel with a gray value between 0.95 and 1.05 times the seed pixel’s value, which also satisfies the connectivity criterion, is included in the region. The reason for using this type of growth tolerance is found from a closer examination of the definition of contrast. Seed-fill region growing results in regions having contrast greater (in magnitude) than a certain minimum contrast, \( C_{\text{min}} \). We require this minimum contrast to be independent of region gray level, so that the results of enhancement will be independent of a multiplicative transformation of the image. A region of minimum positive contrast \( C_{\text{min}} \) will have a mean foreground value of \( f \) and a mean background value of \( (1 - \gamma) f \). The minimum contrast, \( C_{\text{min}} \) is then, using (2),

\[
C_{\text{min}} = \frac{f - (1 - \gamma)f}{f + (1 - \gamma)f} = \frac{k}{2} \approx \frac{k}{2} \tag{8}
\]

and we see that the contrast \( C_{\text{min}} \) is independent of the foreground gray level or background gray level. It depends only on the region growth tolerance parameter \( \gamma \), and is in fact approximately one half the growth tolerance, for small \( k \). Weber’s ratio of 2% for a just-noticeable feature suggests that the growth tolerance should be at the most 4%, to grow regions which are not noticeable prior to enhancement (and are subsequently enhanced to a contrast above the Weber ratio). A lower bound on \( k \) may be established empirically.

C. Contrast Enhancement

Equation (2) defined a region’s contrast as a function of the mean gray levels of the foreground \( f \) and background \( b \). Contrast can be increased by changing \( f \) or \( b \). Rearranging (2), and replacing \( C \) with an increased contrast \( C' \) gives

\[
f' = b \frac{1 + C'}{1 - C'} \tag{9}
\]

where \( f' \) is the new foreground value. In the algorithm developed, only the seed pixel and the redundant seed pixels
in the foreground take this value. The remaining pixels in the foreground (i.e., not the region’s seed or redundant seed pixels) obtain new values when they in turn act as seed pixels and are used to grow different regions. (If all pixels in the foreground were replaced by \( f' \), the output image would depend on the order in which regions were grown, and details within each region would be lost.) The new contrast \( C' \) for the region can be calculated using an analytic function of \( C \) or an empirically determined relationship between \( C' \) and \( C \). Previously, analytic functions (square root, exponential, and logarithm) were used [9], [42], however we have found that an empirically formed chart or plot defining the relationship between \( C' \) and \( C \) gives better results. A typical example of such a plot is presented in Fig. 3. This curve was specially designed to boost perceptibility of regions with low-to-moderate contrast while not affecting high-contrast regions. It was selected in consultation with an experienced radiologist (JELD) from a set of contrast enhancement curves (plots of \( C' \) versus \( C \)) which produced varying degrees of contrast enhancement.

**D. Evaluation of Enhancement**

The improvement in images after enhancement is often very difficult to measure. A processed image can be said to be an enhancement over the original image if it allows the observer to better perceive the desirable information in the image. In mammograms, the improved perception is difficult to quantify. Use of statistical measures of gray level distribution as measures of local contrast enhancement (for example, variance or entropy) have not been particularly meaningful for mammogram images. A number of images which clearly showed improved contrast showed no consistency, as a class, using these statistical measurements. A new measure which we propose here, and which has greater consistency than the statistical measures, is the contrast histogram. The contrast histogram is a graph of the distribution of contrast over the image. If we measure the contrast of all regions (as obtained by the region growing procedure described earlier) in the image, prior to enhancement and subsequent to enhancement, the enhanced image’s contrast histogram should contain more regions at higher contrast levels than the original image’s contrast histogram. Various enhancement methods can be quantitatively compared by measuring the properties of their respective contrast histograms. The width of a contrast histogram can be quantified by taking the second moment about the zero contrast level. Specifically, for a distribution of contrast values \( c_i \), quantized so that there are \( N \) bins between -1 and 1, the second moment \( M_2 \) is

\[
M_2 = \sum_{i=1}^{N} c_i^2 p(c_i)
\]

where \( p(c_i) \) is the normalized number of occurrences of seed pixels (including redundant seed pixels) which grow a region with contrast \( c_i \). A low-contrast image, that is one with a narrow contrast histogram, will have a low value for \( M_2 \), while an image with high contrast will have a broader contrast histogram, and hence a greater value of \( M_2 \). Image contrast must be measured after the entire image has been enhanced, since the relative contrast between adjacent regions is dependent on the changes made to each of the regions.

To measure contrast in an image after enhancement, region growing (using the same parameters as in the enhancement run) is performed on the output enhanced image, and a contrast histogram is generated. The same procedure is performed on images enhanced using other methods for comparison. In general, the final contrast values in the output image will not match the contrast values specified by the contrast transformation in (9). This is because (9) is applied pixel by pixel to the input image, and the adaptive neighborhood for each pixel will vary. Only if all the pixels in an object have exactly the same gray level value will they all have exactly the same adaptive neighborhood and be transformed in exactly the same way. Thus the contrast enhancement curve is useful for identifying ranges in which contrast enhancement is desired, but not for specifying the final contrast of the regions. The contrast of each region grown in the image is in fact dependent on the value specified by the initial region contrast and the transformation curve as well as the transformation applied to adjacent regions. For example, if two relatively bright regions are adjacent, their enhancement will produce a final contrast lower than that specified due to the transformation of each region. On the other hand, if a dark region and a bright region are adjacent, their enhancement will produce a greater contrast than that specified by the transformation curve. The discrepancy between the contrast transformation curve and the actual contrast values produced is image-dependent, and cannot be calculated during enhancement. A postprocessing analysis by region growing is necessary, and was done to obtain the contrast histograms shown in this paper. Note also that the regions grown at any location in the original image and the same location in the processed image need not be exactly the same even if the same region growing criteria are used.

**VII. ACQUISITION, PROCESSING, AND DISPLAY OF DIGITIZED IMAGES**

Mammogram films were digitized using an Eikonix 1412 scanner (Eikonix Inc., Bedford MA), which digitizes up to 4096 scanlines, each with 4096 12 bit pixels. Films were illuminated by a Planar 1417 light box (Gordon Instruments, Orchard Park, NY). Although this light box is constructed to
have a uniform light intensity distribution, it was necessary to correct for nonuniformities in illumination. After correction, pixel gray levels were determined to be accurate to 10 bits, with a dynamic range of approximately 0.02 to 2.52 optical density units [49].

The images were displayed in whole or in windowed sections on either Sun workstation consoles (Sun Microsystems Inc., Mountain View, CA), or on a MegaScan 2111 monitor (Advanced Video Products Inc., Littleton, MA). The MegaScan monitor displays $2560 \times 2048$ 8 bit pixel subimages at 72 noninterlaced frames per second from a 4096 $x$ 4096 12 bit pixel frame buffer, with interactive zooming, scaling, and panning.

Image processing was performed on either a Sun workstation for small test images, or on a Myrias SPS-2 supercomputer (Myrias Research Inc., Edmonton, Alta., Canada). The Myrias SPS-2 is a parallel supercomputer which uses 64 Motorola 68020 microprocessors running in parallel. Typical processing speeds were 5 ms/pixel on a Sun 3/280 workstation, and 0.5 ms/pixel on the Myrias SPS-2 [11].

Processed images were presented in hard-copy form on a Kodak XL7700 (Eastman Kodak Co., Rochester, NY) digital continuous tone printer. This printer can print $1536 \times 2048$ 8 bit pixel images on transparency material with an optical density range from 0.05 to 2.70. Thus, some down-sampling and loss of resolution occurs when printing images. The Kodak XL7700 printer is connected to the network of Sun computers via a Macintosh Ilci (Apple Computer Inc., Cupertino, CA).

Selection of optimal processing parameters, such as the region growth tolerance and background width, was done using an interactive version of the enhancement program. This version allows intermediate results to be displayed on the MegaScan monitor. Features of interest in the images were selected with crosshairs, and regions were grown using pixels in the selected objects. The foreground grayscale level tolerance was adjusted until a region was grown that matched the object under study, and then used to process images containing similar objects. Region-based processing could also be observed pixel by pixel using this interactive facility.

VIII. EVALUATION OF IMAGE QUALITY IN THE ENHANCEMENT OF DIGITIZED MAMMOGRAM IMAGES

A. Case Studies and Evaluation

Enhancement of mammograms digitized at high resolution is presented in this section. The mammograms are from teaching case studies in the Foothills Hospital radiology library. Contrast histograms and the second moment of the contrast distribution ($M_2$, as defined in (10)) will be used to quantify the enhancement of images presented here. Three test images selected from the total of ten studied so far are presented in this section. These cases represent typical problems in the diagnosis of mammograms. The initial diagnosis made from each mammogram was subsequently verified by biopsy at the time of the patient’s treatment, prior to this study.

B. Contrast Enhancement of a Microcalcification Cluster

Fig. 4(a) shows a part of the digitized image of a mammogram of a 64-year-old female’s right breast. The distinguishing feature in this image is a cluster of calcifications in the upper left portion of the image. These calcifications are linearly distributed, suggesting that they are intraductal. Cancer was suspected because of the irregular shape and size of the individual constituents of the calcification cluster, although hyperdense tissue cannot be clearly seen in this area of the image. A biopsy was subsequently performed on the patient, which confirmed the presence of an invasive intraductal carcinoma. Fig. 4(b) shows the same part of the output image after region-based contrast enhancement was applied to the entire digitized mammogram. The curve shown in Fig. 3 was used as the contrast transformation curve, the growth tolerance was 3%, and a background width of 3 pixels was used. Increased contrast is apparent throughout the image, and subtle details are now visible at higher contrast. The arrows in Fig. 4(a) and (b) highlight two features of interest. Note the sharper edges between features as the contrast of the calcifications has been greatly increased in the processed image. A feature of interest in Fig. 4(a) and (b), a small, isolated calcification, highlighted by the black arrow, is more obvious in the enhanced image. Other similar features in the image have been enhanced to the same degree. The feature near the centre of the image highlighted by the white arrow is possibly the cross-sectional projection of a mammary duct. If this interpretation is correct, the distorted geometry (away from the normally circular cross-section) is indicative of intraductal malignancy. This feature is not readily apparent in the original image. Fig. 4(c) and (d) show the contrast histograms of the complete mammograms from which the images in Fig. 4(a) and (b) were taken. The contrast distribution is plotted on a logarithmic scale to emphasize small features at high-contrast values, corresponding to the regions of interest in the images. The wider distribution and greater occurrence of regions at high contrast values in the histogram of the enhanced image show that it has higher contrast. The second moment $M_2$ for the input image contrast histogram is $3.71 \times 10^{-4}$ and the corresponding value for the enhanced image is $6.17 \times 10^{-4}$, indicating that the contrast spread is wider in the enhanced image.

The enhancement shown in the above case has little immediate practical value, since the characteristics of the calcification cluster in the original image are sufficient to lead the radiologist to recommend biopsy. However, if mammary ducts and other anatomical features become easily visible in the enhanced image, as is suggested here, the extent and degree of disease can be judged more accurately, and the biopsy method and location determined accordingly.

C. Contrast Enhancement of a Dense Mass

Fig. 5(a) shows a portion of a mammogram of a 43-year-old female’s right breast. In the lower right quadrant of the image is a dense mass with diffuse edges and a spiculated appearance (black arrow). Probable presence of calcifications was diagnosed after examination of the film through a hand lens. Fig. 5(b) is the corresponding image after region-based contrast enhancement. The second moments
of the contrast histograms [Fig. 5(c) and (d)] of the two corresponding mammograms are $6.7 \times 10^{-4}$ and $17.0 \times 10^{-4}$, respectively. The interior detail of the mass is much more apparent in the enhanced image, and the bright, irregular details are probably calcifications. Also of interest is the appearance of the dense mass to the left of the spiculated mass (white arrow). It has smooth margins, and a generally benign appearance. After enhancement, bright, irregularly shaped features are apparent in this mass, and may possibly be malignancy-associated calcifications as well. This leads to the diagnosis of a much wider spread in malignancy, which would have affected subsequent patient management.

D. Benign Masses

For comparison with the benign-looking mass in the image discussed in Section VIII-C, an image with a histologically verified benign mass of a similar appearance was enhanced. Fig. 6(a) shows a close-up of a benign cyst in this image. The brighter regions in the center of this mass do not show the irregular outline as those in the previous image did. These bright features are thought to be the result of superimposition of crossing linear supporting tissues. This can be seen by the linear features which cross at the bright points. The corresponding portion from the enhanced image is shown in Fig. 6(b). Few changes are apparent from the original image. The value of $M_2$ for the original image is $7.3 \times 10^{-4}$, and for the enhanced image $M_2 = 14 \times 10^{-4}$, showing that contrast enhancement was accomplished. By examining other areas of the image, the enhancement is apparent. Therefore, since no high-contrast features were indicated in the mass of Fig. 6 after contrast enhancement, we can conclude that the bright, irregular features in the benign-looking mass of Fig. 5 are
indeed calcifications, and not enhancement artifacts.

E. Comparison with Other Techniques

Nonlinear Rescaling: When diagnosing mammograms, the radiologist's attention is primarily concentrated on the brighter areas of the film. If the brighter gray level range is expanded, then features which consist of pixels in this range will show increased contrast. A simple nonlinear rescaling, as defined in (5) with $p = 1.5$ was applied to the digitized mammogram from which Fig. 4(a) was taken, and the corresponding portion of the resulting image is shown in Fig. 7(a). Contrast in the area of the calcification cluster has been increased, at the cost of decreased contrast in the darker areas of the image. Overall image contrast has been decreased slightly, as $M_2$ decreases from $3.7 \times 10^{-4}$ for the original image to $3.2 \times 10^{-4}$ for the processed image. While the enhancement here is not as good as with region-based contrast enhancement, the advantage of this method is its simplicity. It could be implemented as a look-up table in display hardware, allowing real-time enhancement.

2) Unsharp Masking: The $3 \times 3$ unsharp filter mask presented in (7) was applied to the complete mammogram from which Fig. 4(a) was taken. The portion of the resulting image which corresponds to the microcalcification cluster in Fig. 4(a) is shown in Fig. 8(a). Contrast of the calcification cluster is increased, although not to the degree accomplished in the image generated using region-based contrast enhancement. Also, the overall appearance of the image is altered more from the original image than in the region-based image. $M_2$ increases from $3.7 \times 10^{-4}$ for the original image to $4.4 \times 10^{-4}$ for the processed image. Recall that $M_2$ was $6.2 \times 10^{-4}$ for the region-based contrast enhancement image in Fig. 4(a).

3) Global Histogram Equalization: Global histogram equalization was applied to the full mammogram from which Fig. 4(a) was taken. Fig. 9(a) presents the portion of the
equalized image which corresponds to Fig. 4(a). This portion of the image has poor contrast. Equalizing the gray-level histogram for the complete image compresses the gray-level differences in the bright, small regions of the image (which are of the most interest for diagnostic purposes) and expands the gray-level differences in the large, dark regions. Contrast is thus decreased in the areas where the calcifications lie, although global image contrast, as measured by $M_2$, has increased to $1.0 \times 10^{-3}$ from $3.71 \times 10^{-3}$.

IX. PARAMETER SELECTION FOR MAMMOGRAM IMAGES

Selection of the parameters controlling region growing was performed using the interactive program as indicated in Section VII. Areas of interest in test mammogram images were identified with the aid of an experienced radiologist. Region growing parameters were adjusted until the regions grown corresponded to details in the feature to be enhanced. For example, when increased contrast in the internal structure of suspicious dense masses was required, the growth tolerance was specified to grow regions that matched internal structures in a given mass which were identifiable on the initial image. Finding a growth tolerance to satisfy this criterion was not always possible. On the other hand, growing regions which corresponded to microcalcifications was straightforward, because of the sharp boundaries of these features. In images which were used to investigate enhancement of microcalcifications, the growth tolerance was adjusted to prevent the growth of unrealistically large regions in the normal tissues of the breast. A growth tolerance of 3% proved to be suitable in most cases. Background width was increased from the initial background layer found during foreground growing to include a representative sample of pixels surrounding the feature of interest, without including portions of other features of interest. In images where calcifications were the features of
interest, the background was kept narrow, typically 3 pixels wide. An option is included in the enhancement algorithm to reject enhancement if the background gray level fluctuates beyond a specified deviation. For mammogram images, regions which correspond to identifiable features typically have highly uniform backgrounds, and this option was rarely invoked.

X. EXAMINATION OF THE DIAGNOSTIC UTILITY OF MAMMOGRAMS ENHANCED USING REGION-BASED IMAGE PROCESSING

In order to examine the differences in radiological diagnoses that may result from region-based enhancement of mammograms, eight test cases from the teaching library of the Foothills Hospital (Calgary, Alta., Canada) were studied. For each of these cases the pathology was known due to biopsy or other follow-up procedures. For each case a single mammographic film which presented the abnormality was first digitized as described in Section VII, and the digitized mammogram was then enhanced using the region-based contrast enhancement method. For all enhancements, the tolerance for region growing was set at 0.05, the width of the background was set to 3 pixels, and the enhancement curve used was that presented in Fig. 3. The digitized images were decimated for display to approximately 2048 x 1280 with 8 bit pixels. In each case, the original, digitized mammogram was first presented on the MegaScan 2111 monitor. The image occupied about 20 x 15 cm on the screen. An experienced radiologist (JELD), while viewing the digitized original, described the architectural abnormalities which he observed. Subsequently, the enhanced image was added to the display below the original image. While observing both the enhanced mammogram and the original mammogram together, the radiologist described any new details or features which became apparent to him.

Case 1) was that of a 62-year-old patient with a history of diffuse nodularity in both breasts. The mediolateral oblique (MLO) view of the left breast was digitized for assessment. The unenhanced mammogram revealed two separate nodular lesions: one with well-defined boundaries, with some indication of lobular calcium; and the other smaller with poorly defined borders, some spiculation, but no microcalcifications. The unenhanced mammogram suggested that the smaller lesion was most likely associated with carcinoma, however, there was some question about the origins of the larger
A region-based contrast enhancement was applied to the digitized mammogram from which Fig. 4(a) was taken. Only the portion corresponding to Fig. 4(a) is presented in (a). The contrast histogram for the complete enhanced mammogram is presented in (b).

An examination of the enhanced mammogram revealed definite calcium deposits in the larger lesion and some indication of microcalcifications in the smaller lesion. This image suggested carcinoma as the origin of both lesions much more strongly than the unenhanced mammogram. The biopsy report for both areas indicated intraductal infiltrating carcinoma, confirming the diagnosis from the enhanced mammogram (see Fig. 10).

Case 2) was that of a 64-year-old patient. The digitized original mammogram was the cranio-caudal (CC) view of the left breast. The unenhanced mammogram contained two lesions. The lesion in the lower outer part of the breast had irregular edges and coarse calcifications while the other lesion appeared to be a cyst. Examination of the unenhanced mammogram suggested that both lesions were benign. Examination of the enhanced mammogram revealed no additional details that would suggest a change in the original diagnosis. The appearance of the lesions was not far different from that seen in the unenhanced mammogram, however, the details in the internal architecture of the breast appeared clearer, adding further weight to the diagnosis of benign lesions. Excision biopsies carried out at both sites confirmed this diagnosis.

Case 3) was that of a 44-year-old female patient for whom the MLO view of the left breast was digitized. The original digitized mammogram revealed multiple benign cysts as well as a spiculated mass in the upper outer quadrant of the breast. There was some evidence of calcium, but it was difficult to see. There was a dense nodule adjacent to the spiculated mass. Examination of the enhanced mammogram revealed that the spiculated mass did contain microcalcifications. The dense nodule appeared to be connected to the spiculated mass, suggesting a much further advanced carcinoma than that suspected from the unenhanced mammogram. Biopsy reports were available only for the spiculated region and indicated lobular carcinoma. No further information was available to further verify the modified diagnosis from the enhanced mammogram.

Case 4) was that of a 40-year-old female patient whose mammograms indicated very dense breasts. Film of the right breast indicated an area of uniform density. The CC view of the right breast was digitized and enhanced. The digitized original mammogram indicated a cluster of microcalcifications, all of approximately uniform density, centrally located above the nipple. The enhanced mammogram indicated a similar finding with a larger number of microcalcifications visible and some irregularity in the density of the calcifications. Both the original and the enhanced mammograms suggested a similar diagnosis of intraductal carcinoma. The biopsy of this area confirmed this diagnosis.

Case 5) was that of a 64-year-old female patient with a history of a benign mass in her right breast. A digitized mammogram of the CC view of her right breast was examined. The unenhanced mammogram clearly showed numerous microcalcifications that were roughly linear in distribution with some variation in density. The original mammogram clearly suggested intraductal carcinoma. The enhanced mammogram showed a greater number of calcifications, indicating a lesion of larger extent. The variation in the density of the calcium was more evident. A biopsy indicated an infiltrating ductal carcinoma.

Case 6) was that of a 59-year-old female patient whose right CC view was digitized. The original mammogram indicated a poorly defined mass with some spiculations. The lesion was irregular in shape and contained some calcium. The unenhanced mammogram suggested intraductal carcinoma. The enhanced mammogram provided stronger evidence of carcinoma with poor margins of the lesion, a greater number of microcalcifications, and inhomogeneity in the density of the calcium. The biopsy confirmed the presence of the carcinoma.

Case 7) involved the same female patient as in Case 6); however, the mammogram was taken one year later. The digitized mammogram was the CC view of the right breast. The unenhanced view showed significant architectural distortion due to a segmental mastectomy. The unenhanced mammogram showed an area extending past the scarred region of fairly uniform density with irregular boundaries. The unenhanced mammogram along with the patient's history suggested the possibility of cancer and biopsy was recommended. The enhanced mammogram suggested a similar finding, with added...
evidence of some small microcalcifications in the uniform area. A biopsy of the region showed that the mass was in fact a benign hematoma.

Case 8) was that of an 86-year-old female patient whose MLO view of the left breast was digitized. In the unenhanced mammogram, a dense region was observed with some spiculations. The mammogram suggested the possibility of carcinoma and biopsy was recommended. The enhanced mammogram showed the same detail as the unenhanced mammogram with the additional finding of some microcalcifications. This added to the suspicion of cancer. The biopsy of the region indicated intraductal invasive carcinoma with lymph node metastases present.

In each of these eight cases, the overall contrast in the enhanced mammogram was significantly improved. This allowed the radiologist to comment that "much better overall anatomical detail" was apparent in the enhanced mammograms. He repeatedly observed that "overall detail (internal architecture) is improved" in the enhanced mammogram. In all cases, the radiological diagnosis was confirmed by biopsy. In 7 of the 8 cases, the enhanced mammogram added further weight to the diagnosis made from the unenhanced mammogram and the diagnosis was confirmed by biopsy. In one case the enhanced mammogram as well as the unenhanced mammogram suggested the possibility of carcinoma, however, the biopsy report indicated a benign condition. This case was, however, complicated by the fact that the patient history influenced the radiologist significantly. While it is impossible to make a quantitative assessment of the differences in diagnoses from this type of a qualitative comparison, it would appear that a clearer indication of the patient's condition was obtained by examination of the enhanced mammogram. Detailed, objective evaluation of the diagnostic utility of the enhanced mammograms (such as receiver operating characteristics-ROC) with at least four views for each case is required. A larger number of mammograms for which the patient condition is known through biopsy must be used is such a study. This type of analysis is currently under way.

XI. CONCLUSION

This paper has shown the validity of using region-based contrast enhancement to process mammogram images. Using images digitized from mammograms in a radiology teaching...
library, it has been shown that more anatomical detail is visible in an enhanced image using region-based methods than in the original image, and that no significant processing artifacts are introduced. The method has been shown to provide superior results, as measured by contrast histograms, when compared to other well-known techniques for enhancing medical images. The degree of contrast enhancement is easily controllable. Direct contrast enhancement, performed by measuring the contrast of a region and then increasing it to form the output image, was shown to be effective in enhancing images containing features of varying size and shape. A number of region-based analogues to fixed-neighborhood methods for histogram equalization and noise suppression have also been developed and are presented elsewhere [50]. Region-based shape analysis of mammographic features is currently being investigated and has shown some effectiveness in identifying malignancy-associated calcifications in mammogram images. In images of dense breasts, where the contrast between calcifications and breast tissue is low, the method has been shown to identify calcifications more clearly.

Further work is in progress to establish the utility of these techniques by ROC or other analysis of results of enhancement of large populations of mammograms, including the standard complement of four views per subject.

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