Identification of Regions of Interest in Digital Mammograms

Sameer Singh[†] and Reem Al-Mansoori[‡]

Department of Computer Science, School of Engineering and Computer Science, University of Exeter, Exeter EX4 4PT, UK

ABSTRACT

The main purpose of this paper is to compare clustering (region growing) and gradient based techniques for detecting regions of interest in digital mammograms. Such regions of interest form the basis of applying shape and texture techniques for detecting cancerous masses. In addition, the paper proposes a two-stage method, in which gradient based techniques are applied first, followed by a region growing method that will yield lesser numbers of regions for analysis. For this purpose, we first use histogram equalization and fuzzy enhancement techniques to improve the quality of the images and to compare their utility on our mammogram data. Image-enhanced mammograms are then subjected to clustering or to gradient operations (masking) for segmentation purposes. The segmented image is then analyzed for estimating the regions of interest, and the results are compared against the previously known diagnosis of the radiologist. A total of 30 mammograms from the University of South Florida database were used, for which the radiologist's hand-sketched boundaries of the masses were known. The results show that when compared with histogram equalization, fuzzy enhancement techniques are better suited for mammogram analysis, and when compared with gradient based segmentation, region growing segmentation will give a lesser number of regions for analysis without compromising on quality.

[†]e-mail: s.singh@exeter.ac.uk
[‡]e-mail: Mansoori@exeter.ac.uk)

KEYWORDS

mammography, segmentation, enhancement, fuzzy methods, gradient methods, region of interest

1. INTRODUCTION

Breast cancer is the most frequent type of cancer in women worldwide. The expected rate is increasing in many countries, especially in the United States, where cancer is estimated to affect three out of four families. Breast cancer is the major cause of death amongst women in the 35-to-55 age group (15,000 deaths a year in the UK, with 26,000 new cases diagnosed every year (Tarassenko et al., 1995). Kopans (1998) examines several factors that affect the chances of developing breast cancer. In particular, the relation between aging and the probability of developing breast cancer have been investigated by Reobuck (1990), using a sample of 1500 women.

A mass in the breast can be either benign or malignant. Such masses can form as a result of different internal processes that affect the breast in different ways. Examples of benign breast masses are fibrodenomas, fibrocystic disease, atypical hyperplasia of the breast, phyllodes tumor, periductal mastisis, and papillomas (Kopans, 1998). Malignant breast masses can either be confined to the ducts where they are formed or can be invasive, spreading through the channels to lymph nodes and to other distant sites. For cancers that are localized to ducts, the most common examples are lobular carcinoma *in situ* and intraductal carcinoma. Invasive breast cancers can be ductal, lobular, medullary, comedocarcinoma, papillary, scirrhous, or tubular. Mammographically, benign masses are well circumscribed when compared with malignant masses, but generalizing is difficult. In general, unless they are classical representations of well-known types, all detected masses need further analysis.

For detecting and diagnosing breast abnormalities, several ways may be used, such as self-examination and clinical breast exams, mammography, and open surgery (biopsy). Clinicians recommend mammography because it is considered to be safe, less harmful than biopsy, and more accurate than self-examination where the tumor can be detected before it can be felt.

Mammography is considered the best method for the early detection of breast cancer, and the percentage of patients that can be cured at early stages is usually high (Tucker, 1993; Egan, 1998). A detailed description of breast-screening-program facts and figures in England appears in the bulletin of the National Health Service. For the period 1997 to 1998, the results show that mammography successfully diagnosed 6,914 cases of cancer at a rate of 5.9 per 1000 women screened. This figure per 1000 has increased over the years as mammography has improved, and now more cases are being detected at an earlier stage. Some recent developments in breast imaging are discussed by Säbel (1996). The value of mammography is that it can identify breast abnormalities that may be cancerous at an early stage, before physical symptoms develop. Numerous studies have shown that early detection increases survival and treatment options. The American Cancer Society's guidelines for early breast-cancer detection stress mammography and physical examinations. Obviously, many other methods and techniques are used for breast screening, and each method achieves a different level of clarity in presenting breast images.

Nevertheless, mammography is the only technique that has been proven to be effective for breast-cancer screening. One of the main advantages of using mammography is its cheap cost of implementation for a large population of subjects. Because, on average, radiologists screen more than hundreds of films each day, maintaining consistency and accuracy in diagnosis is not easy. Such difficulty means that computer-assisted diagnostic techniques have the greatest hope for improving breast cancer detection and reducing morbidity from the disease.

A typical digital mammography-based system for the detection of breast cancer is shown in Fig. 1. X-ray images are acquired by compressing the breasts within a plate. Most hospitals take two views, called the Medio-Lateral Oblique (MLO) view and the Cranio-Caudal (CC) view, of left and right breasts. The x-rays are scanned by a digital scanner whose optical characteristics are directly related to the quality of the digital image that is produced. Unfortunately, directly acquiring digital images is not currently possible, which would eliminate some of the problems that we have with analogue-to-digital conversion. Enhancement can be performed in either the spatial or the spectral domain. A variety of image enhancement algorithms

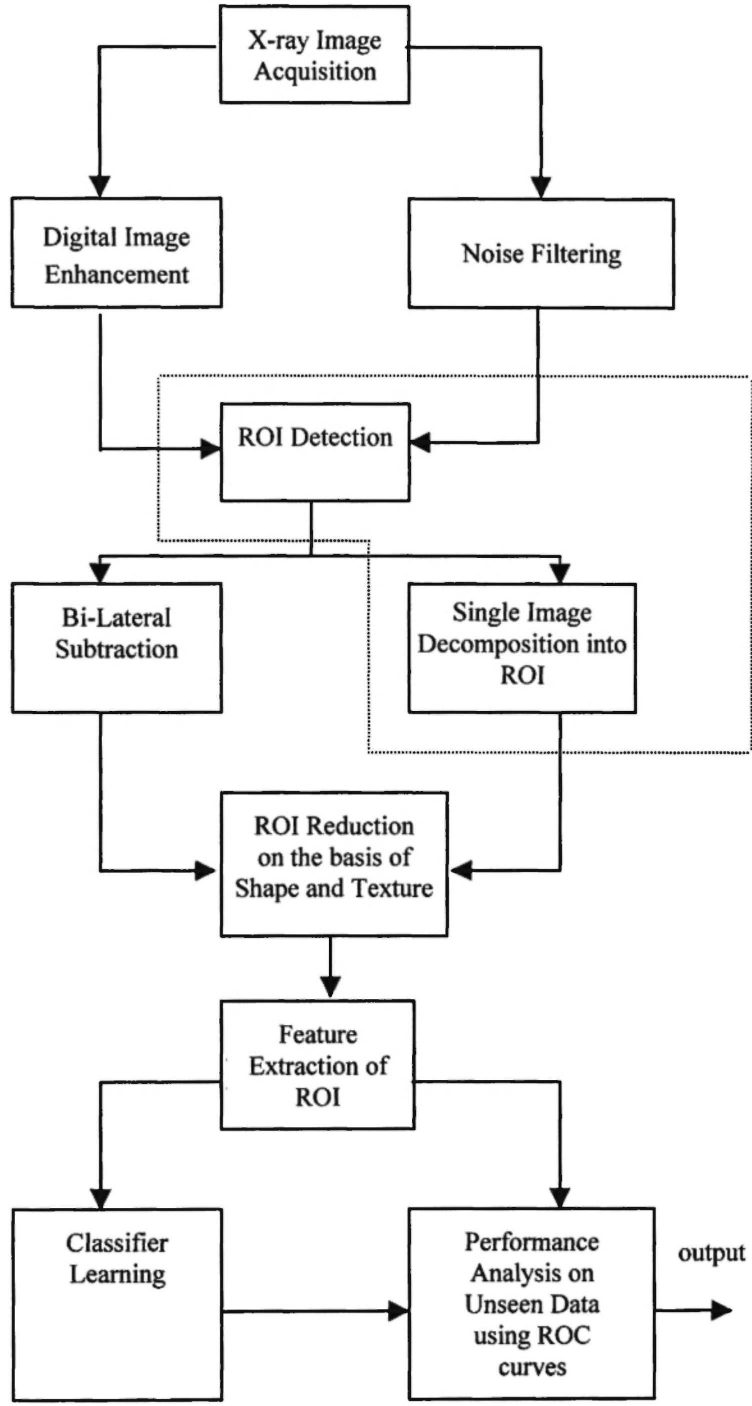


Fig. 1: Digital mammography-based breast cancer detection

are presented by Sonka et al. (1999). If the quality of compression is poor or the scanning mechanism has low resolution, then the signal-to-noise ratio is poor in the resultant images. Noise can be filtered from such images by taking their Fourier transforms and removing high-frequency components before taking an inverse to provide enhanced images. The resultant images are expected to be of good quality for detecting abnormalities using digital image processing. The next step is to find regions of interest (ROI) that need further investigation to determine if they represent some form of abnormality. Two common methods of isolating ROI are used. These methods are bilateral subtraction and single-image decomposition into ROI. Bilateral subtraction techniques align left and right breasts taken with the same view, using landmark information (for example the position of the nipple) and find differences between the two breasts by subtracting one image from another. Asymmetries are widely thought to represent possible areas of abnormality and represent good starting points for analysis. The weakness of this approach lies in the absence of accurate landmarks for aligning images, and the two breasts can be differently imaged giving grey-level differences. The single-image decomposition approach assumes that uniform regions within an image require detailed investigation. Most masses when imaged show as regions with uniform grey-level intensity. These regions of uniform intensities can be detected by pixel clustering. Using both methods, the aim is to have a set of regions that must ideally contain the abnormality, if it exists. Region detection methods in themselves are not capable of judging the label of a region (normal or abnormal). Further shape or texture techniques must be applied to find this. Nevertheless, ROI must be first detected to compute features from them; to do feature extraction for all parts of the image would be highly uneconomical. From the computational point of view, a good image segmentation system should yield a small number of regions that have a higher probability of being the cases that we are seeking when compared with many regions that have a low probability of being abnormal. In practice, shape and texture measures can be used to eliminate those regions that appear unquestionably normal. For example, if regions are over a fixed size or have shapes that are hardly representative of masses, then such regions can be eliminated from analysis. For each ROI, a set of features is extracted for its shape and texture. Haralick (1973) describes a set of 14 measures that can be used to characterize the texture of a region; Sonka et al. (1999) describe a range of shape measures that can characterize the boundaries and area characteristics of regions. If known labels for a given set of regions within images exist, then their feature vectors can be used to train a classification system. Ideal candidates for these include neural networks, nearest neighbor classifier and decision trees. The ability of the system to find the correct features and generalize during classification is measured using ROC curves (see Metz, 1978).

In this paper we focus on ROI detection and single image decomposition into ROI using edge detection methods and a fuzzy clustering technique. The paper is organized as follows. In Sec. 2, we present the standard histogram equalization method of image enhancement alongside our proposed fuzzy enhancement method. The results for their comparison are discussed showing the superiority of the fuzzy technique. In Sec. 3, we evaluate two different techniques for ROI determination. Image segmentation using edge operators is based on the use of Sobel edge detector. Regions of interest have uniformity in their pixel grey levels and yield very few edges if the thresholds are correctly set, whereas other regions yield a very large number of edges in mammograms. By removing all edges within the original image, we are left with ROI. A fuzzy clustering method is then used to identify regions of homogeneous intensities. In Sec. 4 we detail the experimental results obtained on the University of South Florida mammography database. In the Conclusion, we emphasize the superiority of fuzzy enhancement techniques for digital mammogram processing and suggests the use of region growing techniques as a good segmentation technique.

2. MAMMOGRAM ENHANCEMENT

Tumor detection in digital mammograms through image processing is a difficult task for the following reasons:

1) The intensity levels vary greatly across different regions in a mammogram, and features for segmentation are hard to formulate.
2) Subtle grey-level variations across different parts of the image make the segmentation of tumor areas by grey level alone difficult.
3) Tumors are not always obvious, especially where they are subtle or extremely subtle under the glandular tissues, which makes the task of interpretation difficult even for the radiologists themselves.

Mammographic image analysis is a challenging task because poor illumination and high noise levels in the image can vary up to 10% to 15% of the maximum pixel intensity. Such variation is a problem because the image enhancement process may undesirably enhance the noise component in the image (Highnam et al., 1996). Hence, mammograms are among the most difficult images to analyze and interpret (Ruiz et al., 1996). Moreover, the image always seems cluttered, and the background varies greatly between different breasts. Even the worst abnormalities appear quite subtle and irregular.

Our data include two types of breasts: dense breasts and non-dense breasts. Dense breasts were the most difficult to analyze. The tumors in these images are often occluded under the glandular tissues, which makes the process of boundary detection a difficult task. The non-dense breasts are easier to analyze because less fatty and glandular tissue makes the tumors easily distinguishable from other parts of the breast.

The objective of image enhancement is to accentuate or sharpen image features, such as edges and boundaries, by increasing the luminance contrast to produce a clearer image for display and analysis. The information contained intrinsically in a mammogram is limited because of noise. In this paper, we use two methods of image enhancement: the fuzzy plane method and histogram equalization. We finally settled on using the fuzzy plane method as it produces better enhancement.

2.1 Histogram Equalization

Histogram equalization is a widely used and well-established method of enhancing such images as x-rays and landscape photographs that are taken under poor illumination (Pal et al., 1981). This method involves increasing the dynamic range of pixels by stretching their grey-level probability distribution. It is usually observed that by increasing the contrast in such images, the edge detection task becomes easier (Gonzalez et al., 1983). The histogram equalization technique will be used in this study for comparison with the fuzzy technique because histogram equalization is a widely used method and has been widely applied to x-ray images (Pal et al., 1981; Pal et al., 1986).

2.2 Fuzzy Image Enhancement

Fuzzy image enhancement is based mainly on grey-level mapping into a fuzzy plane, using a membership transformation function. Let u_r and u_s denote any pixel's grey-level in the original and enhanced image respectively, and suppose that for every pixel with level u_r in the original image, a pixel is created in the enhanced image with level $u_s = T(u_r)$. Here T is the image transformation function in the spatial domain. The aim is to generate an image of higher contrast than the original by giving a larger weight to the grey levels that are closer to the mean grey level of the image than to those that are farther from the mean.

Pal and Majumder (1986) suggest that we can transform an image plane into its fuzzy plane using a fuzzy transformation function *F*. Each pixel in the original image f(x,y) is mapped to its fuzzy plane value P(x,y). The fuzzy plane is then manipulated using arithmetic operator *A* toward the purpose of contrast stretching. The modified fuzzy plane can be inverse transformed F^{1} to produce a new image f'(x,y) that is enhanced. The arithmetic operator *A* can be chosen for either contrast or smoothing. The process can be represented as:

$$F[f(x,y)] \rightarrow P(x,y)$$

$$A[P(x,y)] \rightarrow P'(x,y)$$

$$F^{1}[P'(x,y)] \rightarrow f'(x,y)$$

Pal and Majumder (1996) have outlined a general method of image enhancement, allowing the experimenters to find a reasonable choice of the operator A for their application. The transformation function A for transforming the original image into the fuzzy plane requires a membership function *F*, and we use the one suggested by Zadeh (1965). The possibility distribution of the grey levels in the original image can be characterized using five parameters: (α, $\beta 1$, γ, $\beta 2$, max) as shown in Fig. 2, where the intensity value γ represents the mean value of the distribution, α is the minimum, and max is the maximum. The aim is to decrease the grey levels to below $\beta 1$ and above $\beta 2$. Intensity levels between $\beta 1$ and γ, and $\beta 2$ 1 and γ are stretched in opposite directions towards the mean γ.

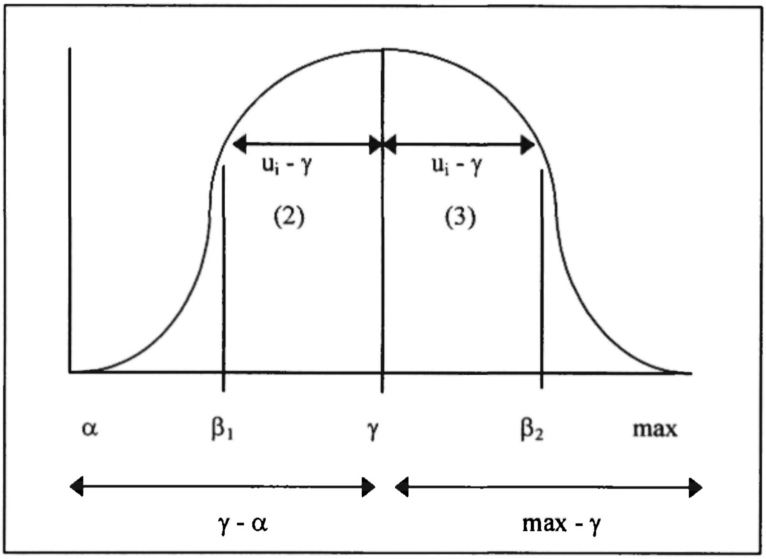


Fig. 2: Possibility distribution function for calculating membership values

The fuzzy transformation function for computing the fuzzy plane value P is defined as follows:

α = min ; $\beta_1 = (\alpha + \gamma)/2$; $\beta_2 = (\max + \gamma)/2$; γ = mean ; max;

1) If $\alpha \leq u_i < \beta 1$; then $P = 2((u_i - \alpha)/(\gamma - \alpha))^2$ (1)

2) If $\beta_1 \leq u_i < \gamma$; then $P = 1 - 2((u_i - \gamma)/(\gamma - \alpha))^2$ (2)

3) If $\gamma \leq u_i < \beta 2$; then $P = 1 - 2((u_i - \gamma)/(\max - \gamma))^2$ (3)

4) If $\beta_2 \leq u_i \leq \max$; then $P = 2((u_i - \gamma)/(\max - \gamma))^2$ (4)

where $u_i = f(x,y)$ is the *i*th pixel intensity.

In our case P(x,y) is given by Eqs. (1) to (4), depending on the pixel's grey level. The operator A used is a square operator, and the inverse operation is given by:

$F\text{-}1[P'(x,y)] = P'(x,y).f(x,y)$

In their study, Pal and Majumder(1986) studied the performance of the fuzzy enhancement technique and compared it with the histogram equalization technique for the enhancement of an x-ray image of one part of the wrist. Their results showed that with the fuzzy method, the contours were easier to detect as the ill-defined cross-over points become more precise. In contrast, the task of interpretation with the histogram modification technique was more difficult, where the image seems to have more wiggles because of noise amplification. In addition, the cross-over points may be ill-defined by the valleys of the histogram, which makes the task of detecting the segments and contours very difficult.

2.3 Enhancement Comparison

Theoretically speaking, both the fuzzy and the histogram equalization methods are aimed at enhancing the quality of the mammogram. The histogram equalization method achieves this aim by stretching the probability distribution of pixel intensities, whereas the fuzzy plane method achieves this goal by arithmetic operations in the fuzzy plane before an inverse transform. Pal and Majumder (1986) present in great detail the advantages of the fuzzy method over the histogram equalization method on a range of applications. Our results shown below support their previous finding on mammogram analysis. Visually, the better enhancement provided by the fuzzy technique is shown in Fig. 3.

The histograms of the enhanced images for the two techniques are shown in Fig. 4. It can be seen that the fuzzy technique compresses the highest frequencies to lie around the mean, whereas the histogram equalization technique stretches the histogram. The Experimental section discusses quantitative measurements on finding how different the two techniques are in their enhancement capabilities on our data.

3. REGIONS OF INTEREST (ROI) DETERMINATION

In digital mammograms, it is often useful to highlight ROI. Regions of interest, in most cases, will isolate the parts of the breast image that are of further interest to the radiologist. These ROI can be highlighted using

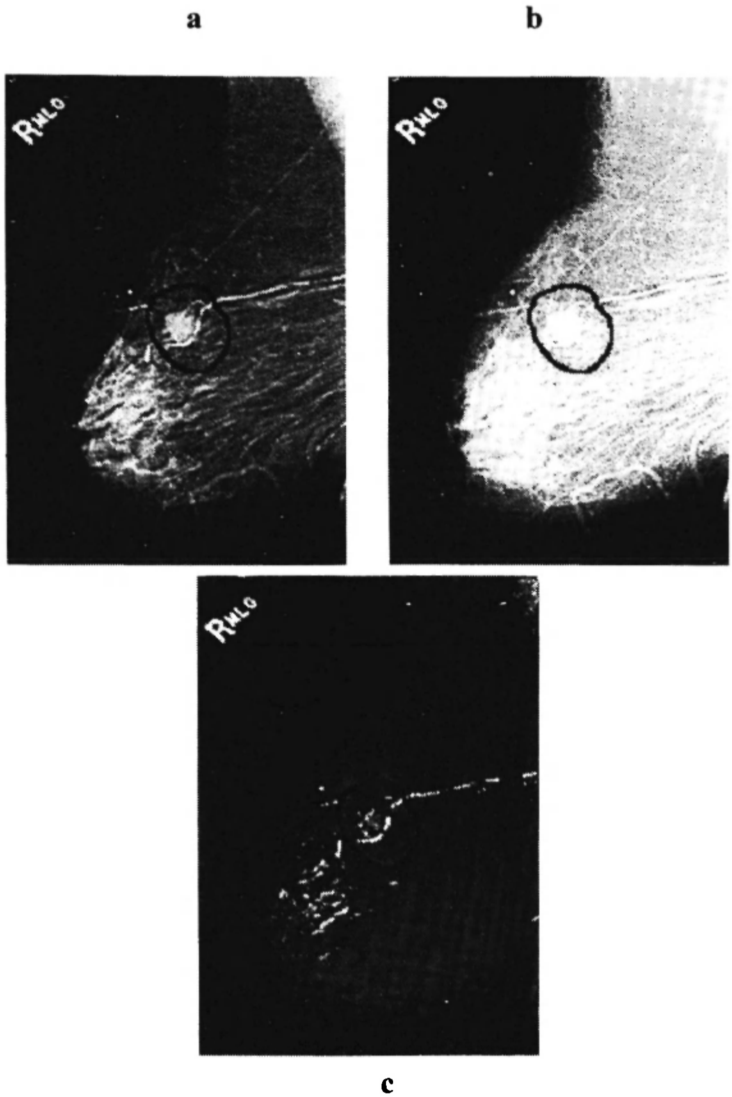
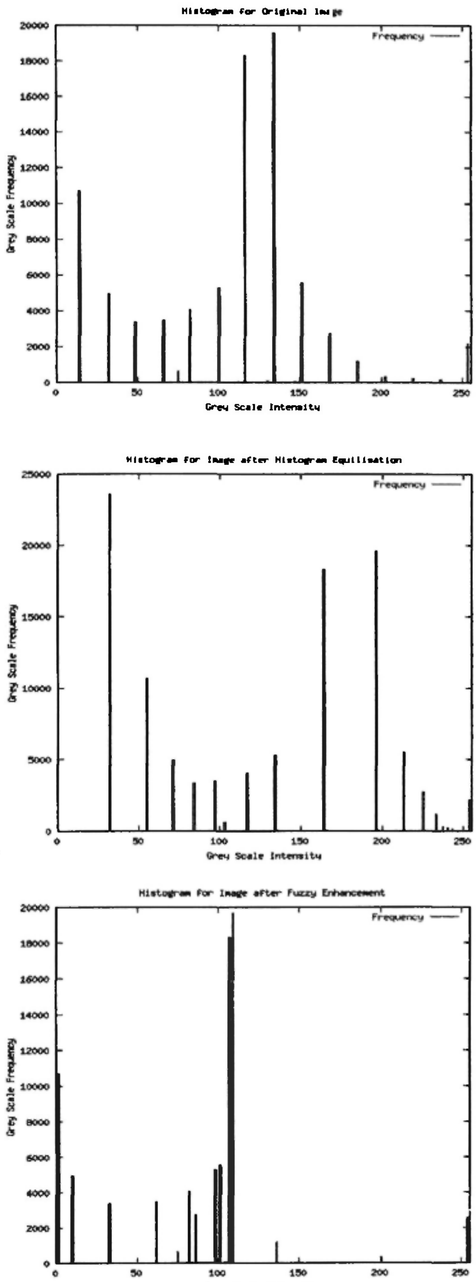


Fig 3: (a) The original mammogram C005; (b) Histogram equalization enhancement; (c) Fuzzy plane enhancement



a b c

Fig. 4: Grey-level distributions: (a) Original image; (b) Enhanced image using histogram equalization; (c) Enhanced image using fuzzy plane method

segmentation techniques in image processing. There are several reasons why we should want to detect such regions:

- Regions of interest highlighted using pseudo-color analysis make the diagnosis easier.
- These regions can be x-rayed in greater detail for more information.
- The changes to these regions can be used for monitoring the effects of therapy.
- Automated analysis of breast cancer can be carried out if details on shape, texture, and spectral information for these regions is available.

Computerized analysis in this manner can be used for training new radiologists on unseen cases.

The fundamental technique for segmenting an image consists of dividing the grey levels into discrete bands and determining a threshold to determine regions or to obtain boundary points (Gonzalez et al., 1983; Pal et al. 1981). Pal et al. (1986) suggest that either a "min." or "max." operator can be used for edge detection, where the difference between them can be considered as a threshold. The histogram of the image can also provide a good indicator, where peaks and valleys can be used for selecting a threshold (Jain, 1995).

The basic methods for segmenting an image involve the selection of an appropriate threshold and the examination of the difference between two successive pixels. If the difference exceeds the threshold, then this information is used for detecting a boundary or edge; this method is classified as a point-dependent technique (Gonzalez et al., 1983). The Prewitt, Sobel, and Isotropic gradient operators compute horizontal and vertical differences of local sums. Compass operators are advanced techniques that measure gradients in a selected number of directions, such as the Kirsh operator (Jain, 1995).

Edge extraction techniques are useful for locating boundaries or regions, whereas for extracting image features it is necessary to group pixels into similar regions. Region-dependent techniques permit an alternative method of segmentation of an image into regions, based on regional properties.

Basu (1987) classified the region detection techniques into three different categories:

1) Local techniques: pixels are placed in a region on the basis of their properties or their neighborhood properties.

2) Global techniques: pixels are grouped into regions on the basis of the image pixel properties.
3) Splitting and Merging techniques: these techniques use graph structures to represent regions and boundaries.

The most common type of local techniques examine the grey-level difference between the neighboring pixels. This intensity gradient is checked to see if it exceeds a pre-defined threshold. The intensity gradient is calculated along a different axis through the pixel of interest in a pre-defined window of a local area (Porter et al., 1997).

Basu (1987) used a set of local and global attributes in his work on image region detection. The local attributes include the maximum contrast in the window, minimum or maximum grey-level value in the window, and the total variation of the centre pixel of the window. In contrast, global attributes measure the total variation of pixels in the window and the average grey-level value of each neighborhood window. Basu suggests that the local attributes represent how well the pixels in a window fit into the definition of a region, whereas the global attributes indicate if this window is a part of the surrounding region.

Another approach discussed by Lifshitz et al. (1990) is based on fixed intensity. They use a hierarchical approach for multi-resolution image description and segmentation. The tree structure of image segments and image description is calculated on the basis of the local intensity. The image is decomposed into light and dark spots, and each level in the tree structure represents a slightly blurred version of the previous one. The root of the description tree represents the original image. The same principle was used by Hutt (1996), where a fuzzy pyramid linking algorithm was used to detect microcalcifications in mammograms. The links between the various levels were determined by a fuzzy membership function. The pyramid structure is formed by producing images of decreasing resolution with the highest resolution image at the bottom of the pyramid (Reed et al., 1993).

An image segmentation technique that is based on region clustering was proposed by Tarassenko et al. (1995). The mammogram is partitioned into clusters on the basis of data density. In each region, the probability density is calculated using the Parzen estimator, and the result of the image segmentation procedure is an image containing all possible ROI. The ROI are then presented to the human expert for further analysis.

The methods discussed so far deal primarily with digital image processing at a global level. We now focus on a more detailed description of the image components. In image analysis and pattern recognition, image segmentation is a fundamental process whose aim is to partition the image space into meaningful regions. The simplest case is having only two regions, an object region and a background region. The usual worry in the segmentation process is partitioning the image into regions without knowing what these regions represent (Niblack, 1986). This problem is difficult because masses can be present in different shapes and forms. At present, we do not have a good understanding of what a segment object in image corresponds to. The only cues to understanding ROI are based on further analysis on their textures and shapes. Most approaches to segmentation fall under one of the following categories:

- Thresholding.
- Edge detection.
- Region detection.

3.1 Thresholding

One of the simplest approaches for segmenting an image is to divide the grey scale into bands and use the thresholds to determine regions or obtain boundary points. This technique is called Grey-Level thresholding, and it is based on dividing the histogram of an image into two bands, B1 and B2, separated by a threshold T. The band B1 contains levels associated with the background, and band B2 represents the object. To detect regional boundaries when the image is scanned, a change in grey level from one band to the other denotes the presence of a boundary. In our study, we noticed that the brightest level is associated with breast tissues and tumors, whereas the dark levels are associated with the background. From this point of view, the threshold T may be selected using the cumulative histogram of pixel intensity (Jain, 1995). In this procedure, we first construct a histogram of the image and then a cumulative histogram on its basis. The cumulative histogram plot at grey level L shows the total number of pixels that have a grey level of L or less. We select the grey level T for which 90% of the total pixels have grey level of T or less using a grey-level histogram. This level serves as our threshold, which is automatically determined and varies for each image.

3.2 Gradient Based Segmentation

Gradient operators measure the gradient of the image g(x,y) in two orthogonal directions by using a pair of masks, h_1 and h_2, that are moved together on the image. In this study we used the Prewitt, Sobel, and Isotropic operators for computing the horizontal and vertical differences of local sums of the co-occurrence matrix. Further description of these operators can be found in Gonzalez and Wintz (1983). In a uniform region, these operators yield zero gradient. In other regions, if the gradient exceeds some threshold T, then an edge is recognized (Jain, 1995). If proper thresholds are chosen, then it is possible to find all edges that correspond to large pixel variations in the original image over the desired level. These pixel positions in the original image can be removed from the original image (by setting them to zero grey level) to leave us with homogeneous regions, which we can term as ROI. We select the grey level T in the edge image, for which 90% of the total pixels have a Sobel operator output of T or less using gradient histogram. This point serves as our threshold, which is automatically determined and varies for each image. In cases where this threshold leads to less than satisfactory performance, manually set thresholds may be necessary.

3.3 Region Growing Based Segmentation

The alternative technique to segmenting an image is to use regional properties. Clustering that is based on the region growing method groups pixels together on the basis of similarity to extract and represent information from an image. There is a slight difference between a region clustering and a region growing method, in that region growing is based on the assumption that the initial points in each region are available, whereas region clustering techniques are applied directly to search for the region directly without prior information, as follows:

1) Start by scanning the image from top left to find an arbitrary seed pixel that exceeds a threshold T.

2) A region is grown from the seed pixel by adding in neighboring pixels that are similar. A fuzzy similarity measure is used to find the distance between a growing region and neighboring pixels to see if they should be added to the region (Theodoridis & Koutroumbas, 1999). Continue this process for all pixels lying on the outer edge of the region until no more neighbors satisfying the condition are found.
3) When the growth of one region stops, we simply search for another seed pixel satisfying our condition 1 and start again.
4) Find all possible clusters and choose the largest cluster as the region of interest.

4. EXPERIMENTAL RESULTS

For this study we considered a total of 30 mammograms, taken from the University of South Florida's database of mammograms containing cancerous masses[1]. The mammograms were scanned from x-rays with a maximum resolution of 512×512 pixels. For each of the 30 mammograms, the hand-sketched boundary, drawn by the expert radiologist, was given. The data were first pre-processed by applying the fuzzy enhancement technique, as well as the histogram equalization technique. We found that the fuzzy technique outperformed the histogram equalization method on most images and therefore we selected the fuzzy method of final analysis. The justification for this comment is given below.

If we consider the region enclosed within the area drawn by the clinician (mass) to be the target T and a region attached to the target and of same shape outside with a width of 20 pixels as the sampled background B, then we can measure the quality of enhancement by finding how well the fuzzy and the histogram techniques improve the contrast between the target and the background regions to make the detection of target easier. During the enhancement process, our assumption is that the masses (targets) have a higher grey-scale value than that of the background and have lower variance. We expect our enhancement process to do the following: (a) increase the contrast between the target and the background; and (b) decrease the overlap between

[1]http://marathon.csee.usf.edu/Mammography/DDSM/thumbnails/cancers/cancer_05/overview.html

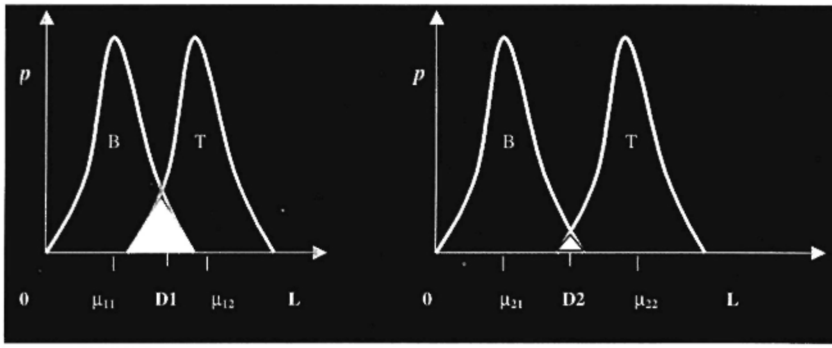


Fig. 5: The grey-level distribution overlap between background B and target T before and after enhancement

target and background grey-level distributions. The following measures can be used for identifying the relative advantages of using the two methods. In Fig. 5 we present a plot showing the overlap between target and background grey levels. In mammography, this overlap is representative of that found between the between the masses and their backgrounds. A good enhancement technique should ideally reduce the overlap, shown as the highlighted region. In particular, we expect that the enhancement technique should help to reduce the spread of the target distribution and to shift its mean grey level to a higher level, thus separating the two distributions and reducing their overlap. The best decision boundary between the two classes for the original image is given by:

$$D_1 = \frac{\mu_{11}\sigma_{12} + \mu_{12}\sigma_{11}}{\sigma_{11} + \sigma_{12}}$$

Similarly, the best decision boundary after enhancement is given by:

$$D_2 = \frac{\mu_{21}\sigma_{22} + \mu_{22}\sigma_{21}}{\sigma_{21} + \sigma_{22}}$$

$$D_2 = \frac{\mu_{21}\sigma_{22} + \mu_{22}\sigma_{21}}{\sigma_{21} + \sigma_{22}}$$

The distance between the decision boundaries and the means of the targets and background, before and after segmentation, is a good measure of the quality of enhancement. This measure, termed *as distribution separation measure DSM*, is given by:

$$DSM = \left(|(D2 - \mu_{21})| + |(D2 - \mu_{22})|\right) - \left(|(D1 - \mu_{11})| + |(D1 - \mu_{12})|\right)$$

Ideally the measurement should be greater than zero; the higher the positive figure, the better the enhancement. For comparing any two enhancement techniques, we should choose the technique that gives a higher value on the *DSM* measure.

In addition to this measure, we use two other measures of contrast analysis with enhancement.

Target to background contrast ratio using entropy

$$TBC_{\epsilon} = \left(\frac{(\mu_T^E / \mu_B^E) - (\mu_T^o / \mu_B^o)}{\epsilon_T^E / \epsilon_T^o} \right)$$

Target to background contrast ratio using variance:

$$TBC_{v} = \left(\frac{(\mu_T^E / \mu_B^E) - (\mu_T^o / \mu_B^o)}{\sigma_T^E / \sigma_T^o} \right)$$

where μ is the mean of a region, σ is its standard deviation, and ϵ is the entropy. The indices E and O refer to the enhanced and the original images, and T and B refer to target and background. It is expected that as a result of enhancement, both measures should give a value greater than zero. When considering a number of images, such measurements can be scaled between zero and one to get a reasonable idea on how well the different images in that set have been enhanced. For regions of uniform intensity, neither of the above measures is directly usable, as the value of σ will tend to be zero. Hence, the above schemes can use an additive constant c to the σ term to avoid division

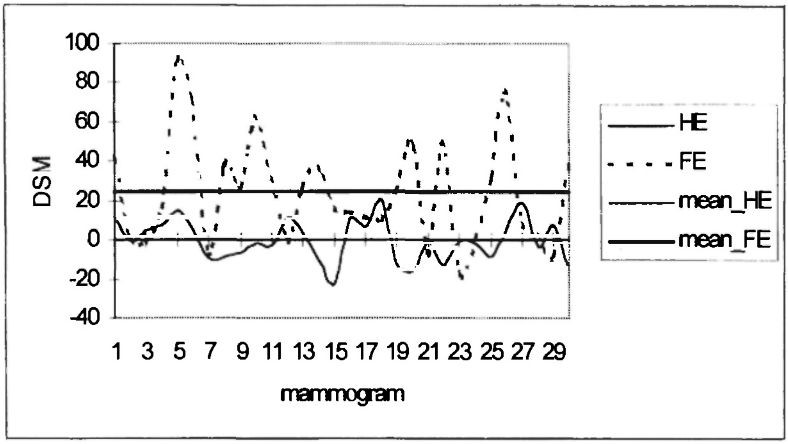


Fig. 6: The Distribution Separation Measure (DSM) for Histogram Equalization (HE) and Fuzzy Enhancement (FE) technique. The mean of the two approaches is also marked.

by zero problems. Ideally, on both measures of contrast we should get high positive values: the higher the value, the better the quality of enhancement.

Figures 6, 7, and 8 show the comparison of the fuzzy and histogram equalization enhancement techniques on DSM, TBC_{ϵ}, and TBC_{v} measures. In all three cases, we have plotted the means over the 30 mammograms alongside the case-by-case measurement. The results show that on all measures, the fuzzy technique outperforms the histogram equalization technique by having a higher score.

The next step is to segment the mammogram using gradient operators and region growing/clustering techniques. For the gradient based methods used in this study, the Sobel's operator gave the best results when compared with the Roberts, Prewitt, and Isotropic operators. In both cases, our main aim is to highlight the ROI and to generate a boundary. We allow for both techniques to find more than one ROI, as identified through the horizontal and vertical scans of the mammogram. In the region growing/clustering technique, we usually pick up the largest cluster as a ROI, but if needed, we can allow the system to pick up the *k* largest clusters in decreasing order of area magnitude. With the gradient techniques, however, all ROI are highlighted; the system could be programmed to prune some of these regions if not needed.

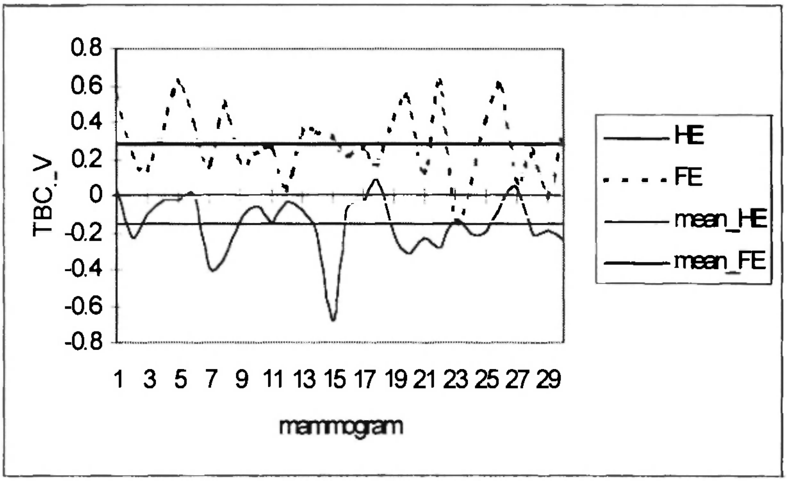


Fig. 7: The Target to Background Contrast using Variance (TBC_V) for Histogram Equalization (HE) and Fuzzy Enhancement (FE) technique. The mean of the two approaches is also marked.

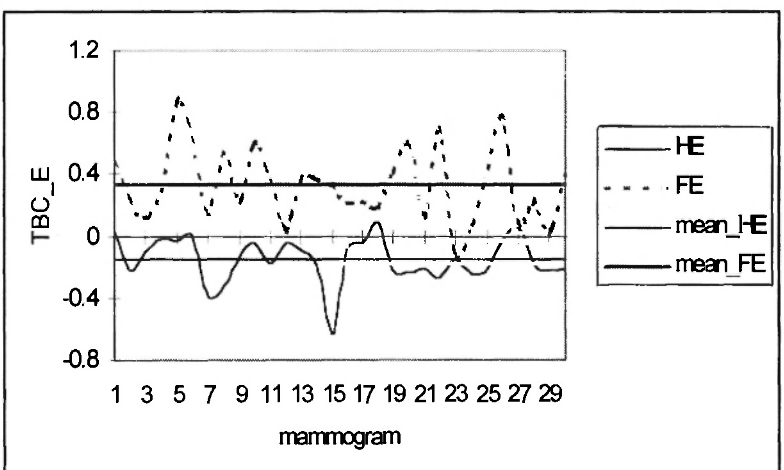


Fig. 8: The Target to Background Contrast using Entropy (TBC_E) for Histogram Equalization (HE) and Fuzzy Enhancement (FE) technique. The mean of the two approaches is also marked.

In this study we show the results on (a) the comparison between gradient based and region growing/clustering techniques for the identification of ROI and (b) the comparison between manual boundary sketches by the radiologist and our selected automated method of boundary determination using a computer. For the first part, we show the actual mammogram results on a selected set of images and for the second part, we show the percentage overlap between the hand-sketched boundary and the computer-generated boundary on the ROI.

4.1 Comparison of Gradient Based and Region Growing Techniques

In Appendix I, we show 12 selected images that are analyzed for identifying the ROI, using both the region growing/clustering technique, as well as the gradient based Sobel's method. The outer boundary of the ROI can be found and displayed by the computer and then compared with that by the human expert; this technique is discussed in the next section. In Appendix I, we show the ROI found by the fuzzy and the gradient based segmentation method. The boundaries generated by the expert radiologists are marked as dark circles, whereas computer-generated boundaries are the outer periphery of the segmented regions shown in white. We have applied stricter rules for the fuzzy technique by using only the largest cluster in our analysis. Clearly the gradient based methods cover a larger area of the image and hence are more likely to include regions that contain masses. In 96.7% of the cases, the regions segmented by the gradient based method contained the actual mass. Similar performance is easily possible using the fuzzy technique, provided that we use k largest clusters rather than just one, where $k>1$. What is remarkable is that by using only the largest cluster on the basis of fuzzy region growing, we identified in 57% of the cases the mass within it. If we had increased the value of k, this accuracy would rise. On the other hand, the gradient based method resulted in tens of regions that would require a lot more processing. The main conclusion is that for a small k, with the fuzzy technique we can perform as good as or better than the gradient method but with the advantage of saving computational time that is wasted on analyzing several unimportant regions.

4.2 Comparison of the Computerized Technique with the Human Expert

We next compare our selected technique (Sobel's operator for segmentation and boundary detection) with the hand-sketched boundaries, drawn by the expert radiologist. As noted before, the Sobel's operator is applied on fuzzy enhanced mammograms for segmentation. The pixels that correspond to the hand-drawn boundaries are manually determined, and a record is kept of their coordinates. The boundaries for computer-calculated segmented regions is determined by finding the pixels that lie on the outer edge of the segmented region. The process is fairly simple. The pixels in the segmented region are first coded with the same grey level and their background with another grey level (white and black for example). For each pixel within the segmented region, we first establish its neighboring pixels and test to see if all of its neighbors are of the same grey level. If not, then this pixel is exposed to the background and lies on the boundary. A record is maintained of all pixels lying on the boundary.

It is interesting to see whether the hand-sketched boundaries correspond well to the computer-generated boundaries. It should be stressed that the hand-sketched boundaries by experts are based on giving a rough idea on where the tumor is, rather than a precise boundary. In Table 1, the percentage overlap (PO) column shows the proportion of overlap between the high-lighted (computer-generated) and circled (hand-sketched) regions. This was calculated as follows:

$$PO = OA/\min(HR, CR)$$

The overlap area (OA) contains the pixels that are common between the highlighted region (HR) and the actual boundary sketched by the radiologist CR (circled area). For most clinical interpretations, we can state that a percentage overlap of >50% represents successful tumor identification. This approach is consistent with the recommendations made by Kallergi et al. (1999). Their study highlighted a range of methods, using what we can objectively quantify as how well the computer-segmented regions correspond to the ground-truth data labeled by a radiologist. The authors state (p. 269): "A detected area is defined as TP (true positive), if there is a certain percent overlap, e.g. at least 50%, between the computer area and the truth file area,

TABLE 1

Statistical details (in pixels) of mammogram analysis using Sobel's method. Percentage overlaps greater than 50% have been italicized.

Image no.	HR/TA	CF	OA	PO
C001	0.16	3620	171	40
C002	0.05	3939	1923	*80*
C003	0.02	3327	243	30
C004	0.07	5667	128	20
C005	0.01	2170	108	30
C006	0.1	3879	644	20
C007	0.08	2137	1998	*100*
C008	0.06	3131	291	20
C009	0.11	4456	3655	*90*
C010	0.1	3286	65	0
C011	0.04	1768	89	10
C012	0.01	2909	210	*50*
C013	0.01	2389	83	30
C014	0.12	3933	656	*50*
C015	0.3	1857	5536	*100*
C016	0.08	1442	208	*60*
C017	0.04	4124	321	20
C018	0.25	3556	59	0
C019	0.03	1862	1120	*90*
C020	0.18	2526	1473	*80*
C021	0.14	5193	227	20
C022	0.1	2551	985	*60*
C023	0.01	2591	612	*100*
C024	0.01	583	490	*100*
C025	0.02	970	861	*100*
C026	0.07	4338	2399	*80*
C027	0.02	3532	13	0
C028	0.13	4035	2997	*70*
C029	0.01	1889	90	20
C030	0.05	1183	2209	*100*

Key: HR: Highlighted Region Area; TA: Total Area; CF: Circumference; OA: Overlap Area; CR: Handsketched Circled Region Area; PO: Percentage Overlap usually a circle or an ellipse or a rectangle drawn around the mass by a radiologist."

The first column in Table 1 details the mammogram index. The second column, HR/TA, shows the proportion of the area occupied by the ROI with the boundary sketched by the computer. The third column, CF, shows the circumference of the boundary estimated by the computer. The fourth column, OA, shows the total number of pixels contained in a region that is common to the hand-drawn ROI and those generated by computer through the segmentation procedure. Finally, the PO column shows the percentage overlap as defined before.

Obviously, for some mammograms the percentage overlap value is equal to 100%, meaning that one of the two regions is subsumed within the other. On the contrary, when the overlap value is equal to 0 in images such as (C010 - C018 - C027), no correspondence was found between the human expert and the computer-generated segmentation of the image. Overlap values between 0 and 1 show the degree of success achieved in identifying the correct segmented regions.

5. CONCLUSION

In this paper we have highlighted two competing approaches to mammogram enhancement, as well as two approaches to their segmentation and boundary detection of tumors. The region growing method of segmentation has been used recently in other studies, e.g. Pohlman et al. (1996), Belhomme et al. (1996), and Petrick et al. (1999). Gradient based methods in the literature have not been used directly for segmentation in most cases, but instead gradient information is used to smooth out images before region growing can be applied. Our study is not primarily directed toward identifying whether a mammogram shows cancer or not; the main aim is to determine ROI accurately. If our aim had been the first one, i.e. to identify and classify tumors as benign or malignant, then we would have used information on the textural, shape, and spectral characteristics of mammograms. We find that the fuzzy enhancement methods, coupled with either gradient based or fuzzy segmentation techniques, are very useful in sketching tumor boundaries in non-dense breasts. This task is not so easy in dense breasts, as exemplified by our failure in some mammograms to correctly identify the ROI. We hope that our results can be improved further by embedding expert knowledge in our segmentation software on subtle tumors in dense breasts. Our further work is now directed at increasing the overlap areas on a large library of mammograms and at using a range of other features for ignoring regions that do not contain cancer.

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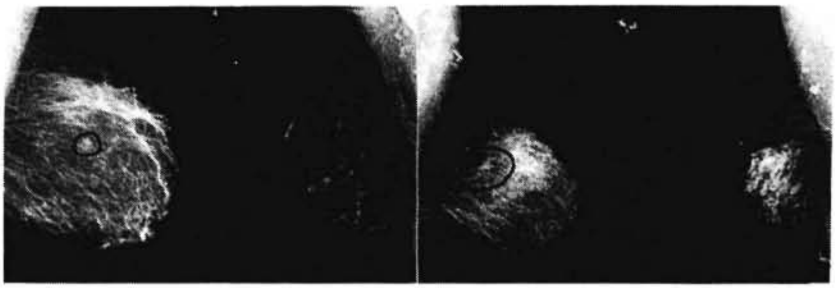
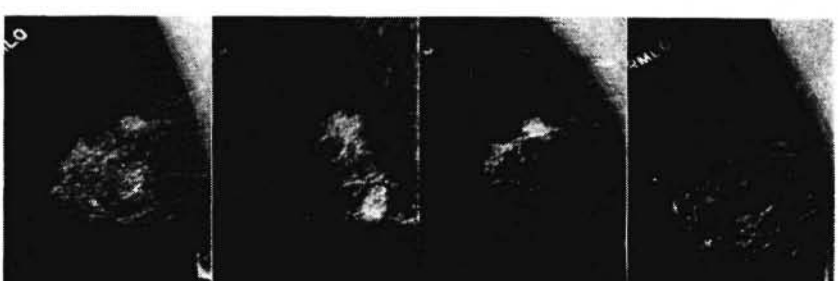
APPENDIX I: COMPARISON BETWEEN GRADIENT BASED TECHNIQUE AND REGION GROWING/CLUSTERING METHOD

IMAGE SET I
(12 Original Images)



C004 C005 C006 C007

C008 C009 C011 C014

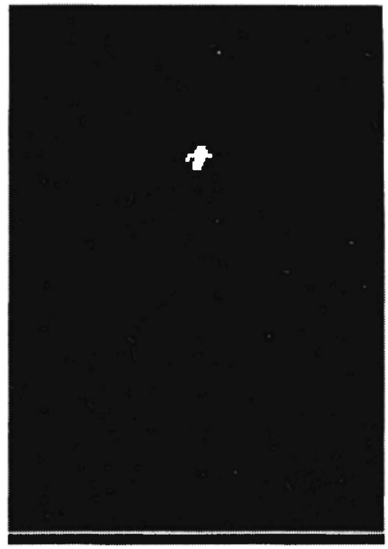


C017 C022 C025 C027

IMAGE SET II

(12 images: Regions of Interest Determined Using Region Growing/ Clustering)

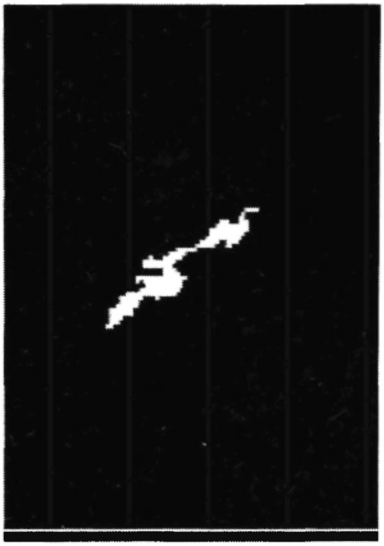
C004



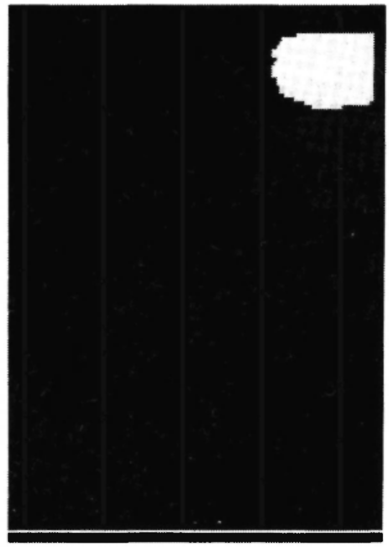
C005

C006

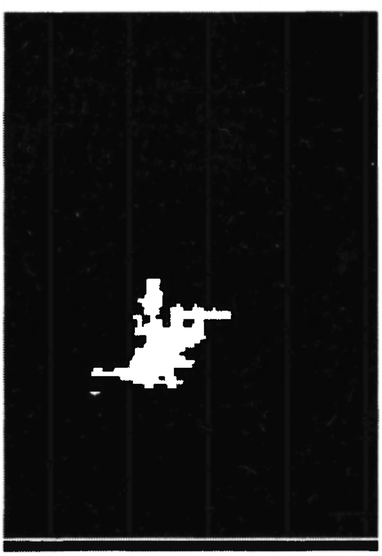
C007



C008

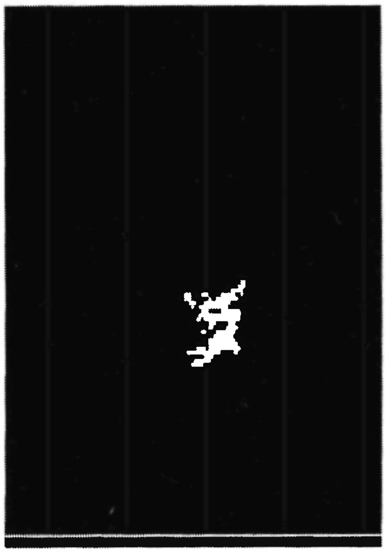


C009

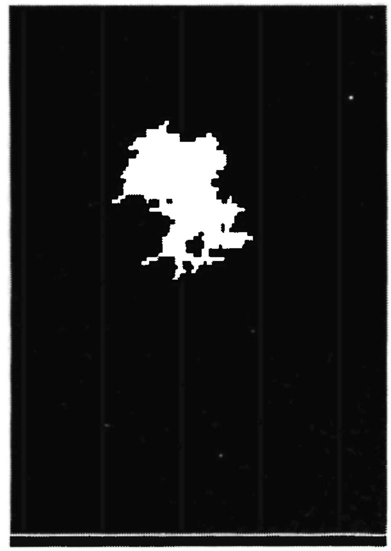


C011

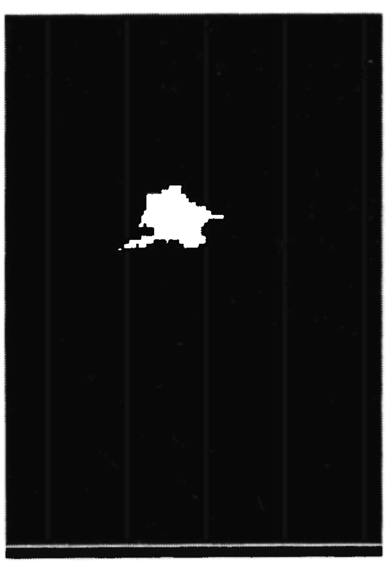
C014



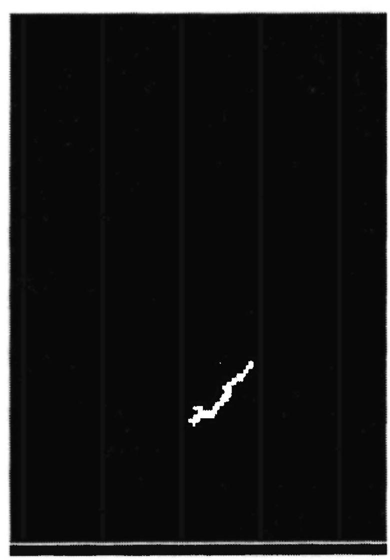
C017



C022



C025



C027

IMAGE SET III

(12 images: Regions of Interest determined using Sobel's operator)

C004

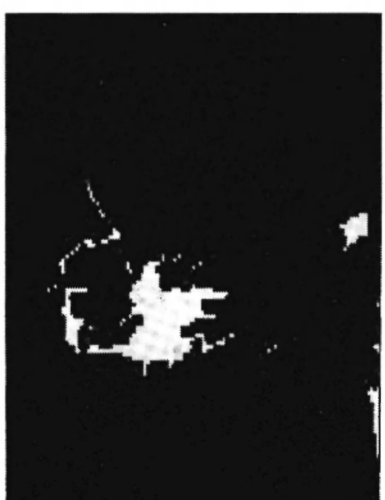
C005

C006

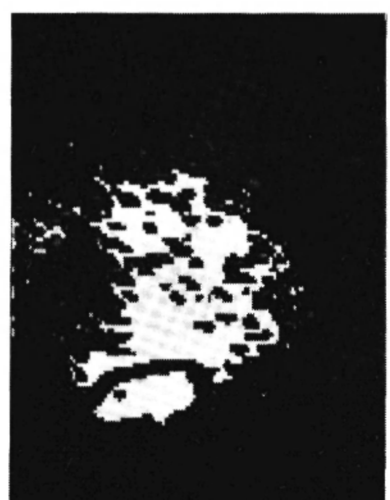
C007

C008

C009

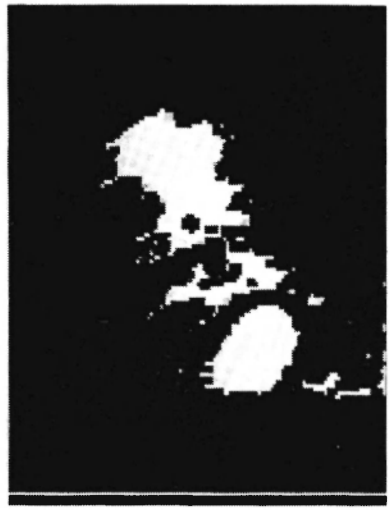


C011



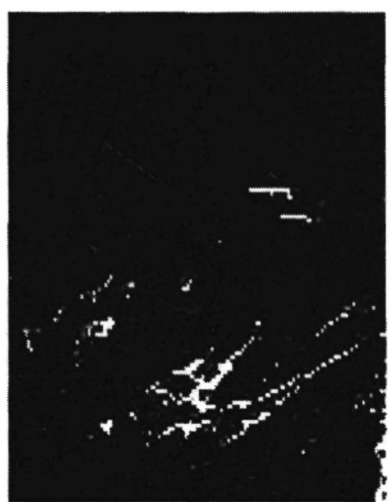
C014

C017



C022

C025



C027