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## DSP IN MAMMOGRAPHY

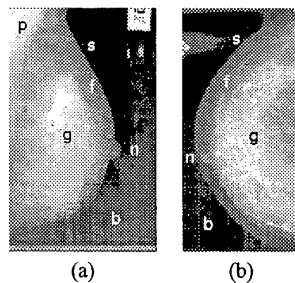
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**Abstract:** Breast cancer is the most frequently occurring cancer in females with no cure at present. Early detection offers the best chance of survival and mammography is used to screen the asymptomatic female population above fifty years of age. Computerized analysis of mammograms can assist radiologists to detect lesions or abnormalities. However, the entire digitized mammogram must first be segmented and analyzed prior to lesion detection. This paper summarizes work done at the Australian Research Centre for Medical Engineering (ARCME) to systematically and hierarchically segment mammograms as a precursor to lesion detection. The breast is first segmented from the non-breast background by polynomial modelling and subtraction of the latter region. The nipple, which is the only anatomical landmark, is then located using a sensitive feature set to search the breast border. The pectoral muscle is then identified by an adaptive edge detection/surface fitting algorithm. Finally, a systematic methodology is proposed for lesion search.

### 1. MAMMOGRAMS

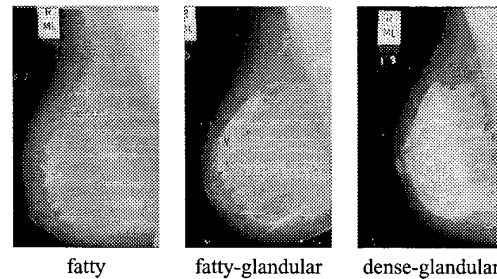
Mammograms are used in many countries to screen populations of women above the age of fifty who have no symptoms, to ascertain if they have breast cancer. Detecting the disease in its early stages improves patient outcome and quality of life. There is much research effort at present to harness computers to assist radiologists in assessing the vast numbers that result from population screening. A standard mammographic examination in Australia involves imaging each compressed breast with X-rays in two views, as illustrated in Figure 1.



**Fig. 1.** A standard mammographic examination in Australia consists of (a) *mediolateral oblique* and (b) *craniocaudal* views for each breast. These mammograms are from different patients and the letters on the images refer to the following: b: non-breast background; s: skin boundary; n: nipple; g: glandular tissue; f: fat; and p: pectoral muscle (visible only in (a)). Note that the nipple is in profile in image (a) but not in (b). These images have been histogram-equalized to improve visibility and are from two different digital mammogram databases: (a) is image mdb003ll from the MIAS database [1] and (b) is image bxrc from the UCSF/LLNL database [2].

When a radiologist views a mammogram, she or he

automatically pays attention to the *breast region*. The image is then assessed for completeness and quality, i.e., whether it is *diagnostically adequate*. Thirdly, the appearance of the breast is gauged to *characterize* it, as shown, for example, in Figure 2.

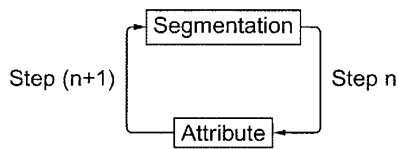


**Fig. 2.** Three mammograms of increasing *radiographic density*, or brightness, from left to right. Fatty tissue appears dark on mammograms; glandular and support tissue appears bright. The bright triangle at the top right corner is the pectoral muscle. The breast region, excluding the pectoral muscle, is called the mammographic *parenchyma*. Mammograms appear more fatty with age.

We are developing an automated system for analyzing mammograms following the radiologists' paradigm: global segmentation, followed by assessment of adequacy, and characterization of appearance. These are important initial steps in a graduated process of successively refined image analysis that logically leads to the detection and characterization of abnormalities, or *lesions*.

### 2. HIERARCHICAL SEGMENTATION

It is difficult to achieve successively refined, hierarchical mammogram segmentation automatically. We have



**Fig. 3.** Cyclic nature of segmentation and mammogram-attribute acquisition. An attribute acquired in segmentation step  $n$  may be used to *drive* the segmentation in step  $(n + 1)$ , or in subsequent steps. The process would exit after the segmentation has been carried out to the required level of refinement.

therefore introduced the *mammogram-attribute database* as a novel tool [3] with which to achieve the goals of segmentation, adequacy assessment and appearance characterization.

This database will comprise those attributes that have been theoretically suggested or experimentally found to be of greatest value in assisting image segmentation, analysis, adequacy assessment and appearance characterization.

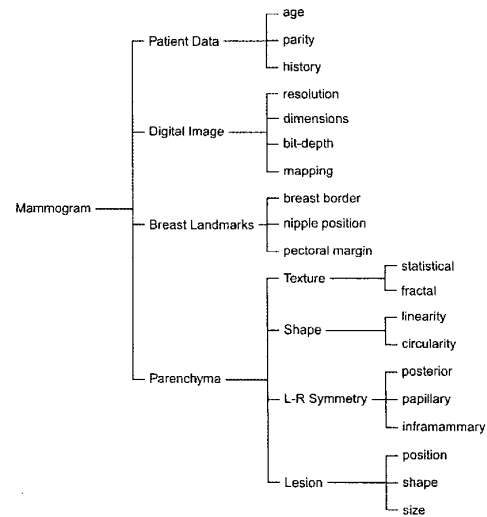
Image segmentation is considered to be an iterative process that progresses from the gross to the subtle. At any step in the segmentation, salient image attributes are identified, extracted and stored in the database. These attributes may be useful in driving the next and subsequent segmentation or analysis steps. This is a cyclic rather than linear process, with the results from one stage feeding into the next as suggested in Figure 3.

A hierarchy of attributes is proposed as shown in the tree diagram in Figure 4. The listed attributes are those we have found useful, although any particular attribute database will, of course, depend on the approach to segmentation and analysis being adopted in that automated system.

The specific steps in the automatic segmentation of mammograms shall be our focus for the remainder of this paper. Nevertheless, the iterative nature of segmentation in the above framework should always be kept in mind.

### 3. EXTRACTING THE BREAST BORDER

Segmenting breast from background is a form of redundancy reduction: once the non-breast pixels are identified, they may be excluded from all subsequent processing, facilitating feature extraction as well as saving processing time. Apart from the overall objective of segmentation, the immediate purpose in extracting the skin-air interface accurately is to provide a suitable input image to a nipple detection algorithm [4]. The requirement to preserve the nipple during segmentation arises from this need. Extracting the breast border is also a prerequisite for bilateral comparison of the left and right breasts. A semi-automatic and fully automatic method for extracting the breast border are now summarized.



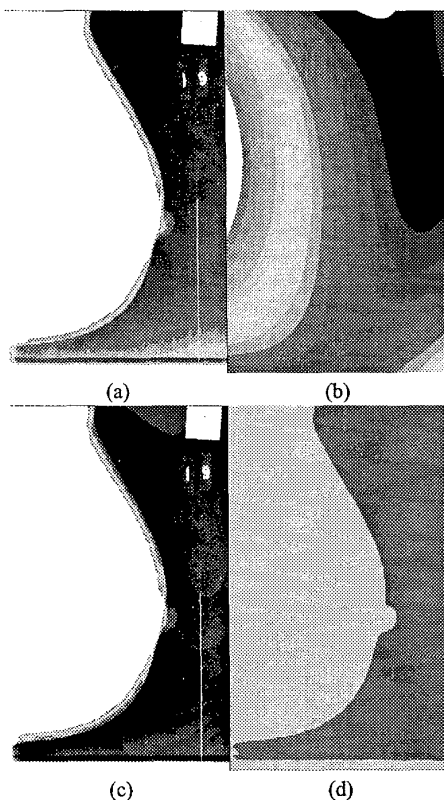
**Fig. 4.** Tree diagram of mammogram-attribute hierarchy. These attributes represent some of those we have found useful and are by no means exhaustive. The third layer is non-specific in that texture, shape, symmetry and lesion-specific attributes are indicated but not spelt out in detail.

#### 3.1. Semi-automatic breast border extraction

The breast and background on a mammogram form complementary, connected sets. Generally, the intensities comprising the background are spatially continuous, low in value and lie within a closed interval. The background may therefore be approximated by a *polynomial* in  $x$  and  $y$ . In the semi-automatic method [5], we include the whole background and a small portion of the breast in the region being modelled. The modelled background is *subtracted* from the original image, the resulting image interactively *thresholded*, and the largest low intensity region taken to be the background. Connected regions are identified, labelled and merged. The background is flood-filled, and inclusions removed from the object, to yield a breast-background binary image. The method has been tested on 58 mammograms of two views from two digital mammogram databases. With one exception, it performs well and yields a skin-air interface with sufficient fidelity to preserve a nipple in profile (see Figure 5).

#### 3.2. Automatic breast border extraction

In the automatic method [6], the mammogram background is again estimated and modelled as a polynomial in two variables. The modelled image is subtracted from the original, re-thresholded and post-processed to yield a binary labelled image, but completely automatically this time. Depending on the value of a new parameter—the *background monochromaticity*—the appropriate degrees of polynomial and values of difference image thresholds are selected to yield accurate breast border images. The method has been applied to the entire MIAS database of

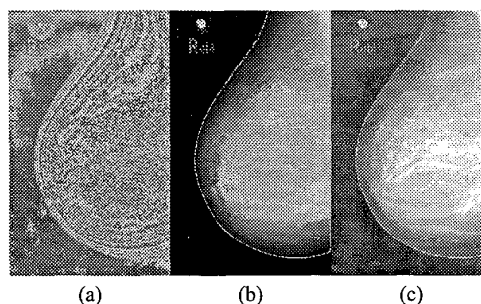


**Fig. 5.** Background Subtraction: (a) original image  $I_0$  with sixteen lowest intensities shown in colour/greyscale and all higher intensities as white; (b) image  $I_m$  of background modelled as a polynomial of degree 3; (c) subtracted image  $I_s$ ; and (d) final segmented binary image  $I_t$ .

322 images. Thirty-two of these were randomly selected, and evaluated by a radiologist who graded 30 (or 94%) of them acceptable (see Figure 6).

#### 4. LOCATING THE NIPPLE

We have developed a simple, fast and accurate method for automatically locating the nipple on digitized mammograms [4] that have been segmented to reveal the skin-air interface. If the average gradient of the intensity is computed in the direction normal to the interface and directed inside the breast, it is found that there is a sudden and distinct change in this parameter close to the nipple. A nipple in profile is located between two successive maxima of this parameter; otherwise, it is near the global maximum. Specifically, the nipple is located midway between a successive maximum and minimum of the derivative of the average intensity gradient; these being local turning points for a nipple in profile, and global otherwise. The method has been tested on 24 images, including both oblique and cranio-caudal views, from two digital mammogram databases. For 23 of the images (96%), the rms



**Fig. 6.** Results of automatic segmentation. (a) Original MIAS mammogram mdb070rl. (b) Segmented breast border superimposed on original mammogram. Because it is difficult to make out the extent of the original image, both the images (a) and (b) were displayed with enhanced gamma when presented to the radiologist for evaluation on a video terminal. (c) The breast border is superimposed on a histogram-equalized version of the original mammogram. The extent of the breast and the non-uniformity of the background are both apparent.

error was less than 1 mm at image resolutions of 400 and 420  $\mu\text{m}$  per pixel.

Results with a nipple in profile and a nipple not in profile are illustrated in Figure 7(a) and (b) respectively. In both Figure 7(a) and (b), the normals to the breast border are shown drawn. The average value of the intensity gradient along the normal is plotted against the  $y$  co-ordinate at the left of both figures.

Note the clear dip in the average intensity gradient at  $y$  values close to where the nipple is in Figure 7(a). This behaviour is characteristic of the nipple in profile and results from the normals traversing tissue corresponding to the protruding nipple, which is an almost uniform, low intensity region on the mammogram. We have consistently found that for our test images, *the nipple position may be estimated reliably and accurately by the mid-point between the positions of the local maximum and local minimum in the derivative of the average intensity gradient.*

When the nipple is not in profile as in Figure 7(b), the position of the nipple may be grossly estimated by the position of the maximum of the average intensity gradient. Indeed, in this case, the mid-point of the positions of the derivatives of the global maximum and minimum intensity gradient respectively equals the position of the maximum intensity gradient. We have chosen to use the mid-point of the global maximum and minimum of the derivative of the intensity gradient to locate the nipple because the maximum, being a single value, may or may not be located symmetrically about these rapid changes in intensity gradient.

#### 5. DELINEATING THE PECTORAL EDGE

The pectoral muscle and its edge appear only in mediolateral oblique view mammograms. It is important as an alignment landmark because the breast is a non-rigid organ that is compressed during imaging. The pectoral

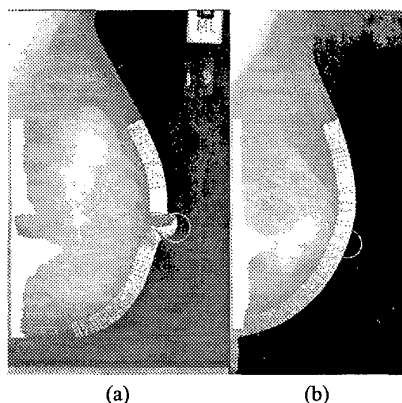


Fig. 7. Results of nipple location for (a) nipple in profile; and (b) nipple not in profile.

muscle attached to the chest wall can therefore function as a landmark for mammogram-pair registration. It is also useful in determining whether enough of the breast has been imaged, i.e., in determining the adequacy of the mammogram, which can be very useful in image quality assurance. Because lesions arise in the glandular tissue, knowing the pectoral margin also allows restriction of the search space for lesion detection.

Our algorithm [7] consists of two parts: straight line estimation, and cliff detection. Although the pectoral muscle edge, or pectoral margin is not necessarily a straight line, it may usefully be modelled as one in a first estimate. The second part embodies refinements to more accurately reflect the possible non-linear contour of the pectoral edge. The search for the true edge is now localized to a neighbourhood defined by the initial straight line estimate, and model-based edge detection and interpolation are used to determine the final edge.

In straight line estimation, iterative thresholding within a region-of-interest (ROI) is used to determine the rough extent of the pectoral muscle. A straight line is then fitted to the margin of the thresholded region, subject to the caveat that the pectoral muscle does not curve outward into the parenchyma. This allows portions of the parenchyma that have been segmented by thresholding to be discarded, and confers robustness to the method. A straight line is then fitted to minimize the square of the error and it is validated independently.

Cliff detection is designed to refine the muscle edge along the straight line estimate, because the actual muscle edge may be slightly curved. Two major components in cliff detection are surface smoothing and edge detection. Surface smoothing is used to remove noise and rough texture on the intensity surface model whereas edge detection is used to find the real shape of the muscle edge within a detection range.

There are several methods to smooth the intensity surface including mean filtering, Gaussian filtering, polynomial fitting and bicubic spline interpolation. Each of these methods was individually tested; it was found that

mean filtering followed by bicubic spline interpolation was most useful for our purpose. Cliff detection assumes a sigmoidal intensity pattern as the intensity surface slopes down at the pectoral margin. Cliff detection has two advantages: intensity rises are ignored and only intensity drops are detected; and by virtue of the fitted model, cliff detection is more robust to noise and bright spots on the image and therefore gives fewer scattered or broken edges.

Results are promising (approximately 94% of images were considered acceptably segmented in a preliminary evaluation) and the spectrum of results is illustrated in Figure 8. In those images where the pectoral muscle is clear and separated from glandular tissues, the resulting curves are very accurate, e.g. (a) and (b). The algorithm is not affected by tapes, as shown in (a), (c) and (d), because the search paths at the top are horizontal. It is also robust to artifacts as shown in (b). In (c), the lower half of the pectoral edge is obscured by other tissues, causing uncertainty in the edge detection. Although the exact muscle edge could not be detected, the straight line estimate was followed, and the final result was acceptable. Note that in this image, there is a strong internal edge inside the pectoral region. It is the same for (d), but the line was fitted to the internal muscle edge in the latter case. The line fitting decision depends on the binary image produced by iterative thresholding. The pectoral muscle in (e) is quite curved, vertically directed in parts, and mostly indistinct, resulting in a poor segmentation. The results are even worse for (f), which is a particularly difficult image.

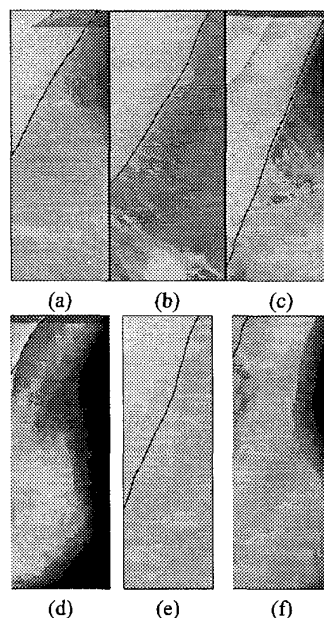


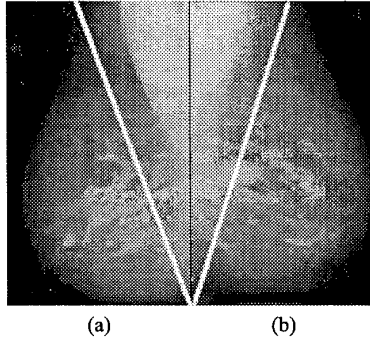
Fig. 8. Results of pectoral margin delineation. Images (a) to (c) are acceptable; (d) to (f) are not.

## 6. SYSTEMATIC LESION SEARCH

Computerized searches must be systematic, complete and repeatable. Raster scan order (left to right, top to bottom) is a favourite automatic search pattern for images. With a mammogram, however, medical practice and anatomy provide compelling reasons for adopting a different but specific search scheme [8].

### 6.1. Paired comparison

The radiologists Tabár and Dean [9] have devised a method for *systematically searching for lesions* that was originally intended for human experts but that is eminently suited for computerization. It relies on *comparing corresponding regions* of the left and right breast mammograms to detect significant differences that could be lesions. Its primary strength is that it is a *relative* rather than *absolute* method and thus factors out natural variability in appearance, which when present, affects both mammograms in a pair in the same way. An example of the Tabár-Dean method is shown in Figure 9.

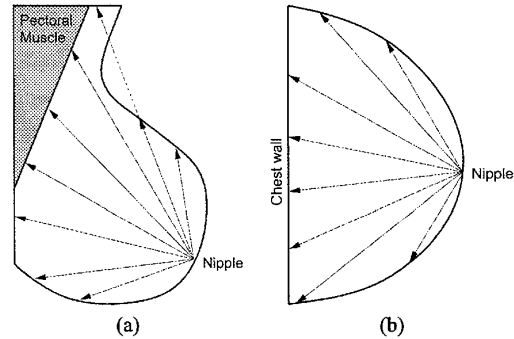


**Fig. 9.** Oblique masking for systematically viewing mammograms according to Tabár and Dean [9]. The images in (a) and (b) are the right and left mammograms from the same patient (MLAS images mdb026r1 and mdb025l1). The regions between the bright pectoral muscle and the slanted arms of the “V” are compared for each side; regions not enclosed by the two arms are blocked out when viewed by the human expert.

### 6.2. Nipple-anchored linear search

The glandular system of ducts in the breast drains into the nipple, which is also its only anatomical landmark. The logical, anatomically-founded search direction is therefore to start at the nipple and fan outward into the breast, excluding the pectoral muscle if it appears on the mammogram. This is illustrated in Figure 10 where the lines represent the search directions and also, to a lesser extent, the *preferred direction* of the *curvilinear structures* on the breast. Any disturbance in the orientation of the curvilinear structures with respect to the search directions may signal a lesion [10]. Incidentally, locating the position of the nipple [4] is a pre-requisite for this search strategy.

It is unlikely that a lesion (except for enlarged lymph nodes) will be found in the region associated with the pectoral muscle. The pectoral muscle is therefore excluded from the lesion search as shown in Figure 10(a), but care should be taken not to miss a lesion close to the chest wall. By the same token the fibroglandular region must be searched thoroughly because this is where breast cancers originate.



**Fig. 10.** Systematically searching for lesions using the nipple as the starting point and fanning into the breast is anatomically well founded. (a) On mediolateral oblique views, the pectoral muscle is excluded from the search. (b) On craniocaudal views the search strategy is similar, but the pectoral muscle is generally absent.

## 7. CONCLUSIONS

The methods of digital signal processing in general, and image processing in particular, may be applied with considerable success in automatically segmenting a mammogram to extract the breast border, locate the nipple, delineate the pectoral margin and thereby set the stage for paired mammogram comparison and systematic lesion search and detection.

Simple techniques may be employed to this end provided the features driving the segmentation are selected to be sensitive and specific to the task. This has been illustrated specifically with the nipple location algorithm. Moreover, the anatomy of the breast may be exploited to advantage to underpin robust and accurate algorithms, as has been illustrated with the breast border extraction and pectoral edge delineation.

By understanding clearly what radiologists do, why, and how, it is possible for engineers to design automatic systems that robustly and accurately replicate what the human expert does.

### Acknowledgements

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## REFERENCES

- [1] J. Suckling, J. Parker, D. R. Dance, and S. A. et al., "The Mammographic Image Analysis Society Digital Mammogram Database," in *Digital Mammography* (A. G. Gale, S. M. Astley, D. R. Dance, and A. Y. Cairns, eds.), (Amsterdam, The Netherlands), pp. 375–378, Elsevier Science, 1994.
- [2] University of California, San Francisco and Lawrence Livermore National Laboratory, (UCSF/LLNL), "UCSF/LLNL High Resolution Digital Mammogram Library." Available from Ms Christine Skillern, Lawrence Livermore National Laboratory, P. O. Box 808, L-452, Livermore, CA 94551, USA; e-mail: <mammo-db-help@llnl.gov>, 1996.
- [3] R. Chandrasekhar and Y. Attikiouzel, "Mammogram-attribute database: A tool for mammogram segmentation and analysis," in *Proceedings of the IASTED International Conference: Signal Processing, Pattern Recognition, and Applications (SPPRA), July 3–6, 2001, Rhodes, Greece* (M. H. Hamza, ed.), (Calgary, Canada), pp. 143–148, ACTA Press, 2001.
- [4] R. Chandrasekhar and Y. Attikiouzel, "A Simple Method for Automatically Locating the Nipple on Mammograms," *IEEE Transactions on Medical Imaging*, vol. 16, pp. 483–494, Oct. 1997.
- [5] R. Chandrasekhar and Y. Attikiouzel, "Gross Segmentation of Mammograms using a Polynomial Model," in *Bridging Disciplines for Biomedicine: Proceedings of the 18th Annual International Conference, IEEE Engineering in Medicine and Biology Society, October 31–November 3, 1996, Amsterdam, The Netherlands*, pp. 1056–1058, Amsterdam, The Netherlands: IEEE, Oct. 1997.
- [6] R. Chandrasekhar and Y. Attikiouzel, "Automatic breast border segmentation by background modeling and subtraction," in *IWDM 2000: 5th International Workshop on Digital Mammography* (M. J. Yaffe, ed.), pp. 560–565, Madison, WI, USA: Medical Physics Publishing, 2001. Proceedings of the Workshop, June 11–14, 2000, Toronto, Canada.
- [7] S. M. Kwok, R. Chandrasekhar, and Y. Attikiouzel, "Automatic pectoral muscle segmentation on mammograms by straight line estimation and cliff detection," in *ANZIS 2001: Proceedings of the Seventh Australian and New Zealand Intelligent Information Systems Conference*, (Perth, Australia), pp. 67–72, ARCME, The University of Western Australia, Nov. 2001.
- [8] R. Chandrasekhar and Y. Attikiouzel, "An expert system schema for lesion search and detection on digitized mammograms," in *NNESMED 2001: Proceedings of the Fourth International Conference on Neural Networks and Expert Systems in Medicine and Healthcare* (G. M. Papadourakis, ed.), pp. 158–162, Technological Educational Institute of Crete, Crete, Greece, 2001.
- [9] L. Tabár and P. B. Dean, *Teaching Atlas of Mammography*. New York: Thieme-Stratton, second revised ed., 1985.
- [10] W. Philip Kegelmeyer Jr, J. M. Pruneda, P. D. Bourland, A. Hillis, M. W. Riggs, and M. L. Nipper, "Computer-aided Mammographic Screening for Spiculated Lesions," *Radiology*, vol. 191, no. 2, pp. 331–337, 1994.