Finding Orientated Line Patterns in Digital Mammographic Images

Reyer Zwiggelaar, Tim C. Parr and Chris J. Taylor
Wolfson Image Analysis Unit, Department of Medical Biophysics
University of Manchester, Stopford Building, Oxford Road
Manchester M13 9PT, UK
reyer@sv1.smb.man.ac.uk

Abstract

In mammography the presence of subtle abnormalities such as stellate patterns and architectual distortions indicates possible malignancy. Radiologists do not always detect these abnormalities in screening mammograms; this has led to interest in computer–aided mammographic interpretation where the radiologist is presented with computer–generated 'prompts' for abnormalities. A first step in this process is the detection of the "orientation", "scale" and "strength" of linear structures in the mammograms. We discuss several generic methods for extracting this information from images and compare their performance using synthetic images intended to simulate the appearance of mammograms. We show significant differences in performance between the different methods. We also show results obtained for real mammograms.

1 Introduction

The UK Breast Screening Programme alone generates 1.5 million mammograms per annum. Potential malignancies can be detected from subtle abnormalities in radiographic appearance but it is known that radiologists fail to detect a significant proportion of these abnormalities. It has been shown that their performance would improve if they were prompted with the possible locations of abnormalities [1]. The abnormalities of interest include microcalcification clusters, masses, spiculated patterns, asymmetry and architectual distortions [2], which can occur either individually or as combinations.

There is a natural division between these subtle abnormalities into patterns of "blobs and clusters" and "lines and structures". In this study we concentrate on the latter group and in particular on stellate lesions which are an important class of abnormality.

Various methods have been described for detecting the patterns of radiating linear structures which characterize stellate lesions [3–5]. They all depend however on obtaining an estimate of line strength, orientation and (sometimes) scale at each pixel. It is this line detection step which we investigate here.

Several approaches to line detection in mammograms have been described. In Section

BMVC 1996 doi:10.5244/C.10.70

2 we discuss five different methods. The effectiveness of these methods in finding the line strength and orientation is assessed in Section 3, where we report the results of experiments performed using simulated line–patterns superimposed on “dense” and “fatty” mammographic backgrounds. In Section 4 the most promising line detection methods are applied to a section of a mammogram which is known to have a stellate lesion present. Both single scale and multi–scale results are presented. Some concluding remarks are made in Section 5. This Section also includes some discussion of future directions.

2 Line detectors

The importance of linear structures in image analysis should not be underestimated and may be as important as the detection of edges. It seems however that line detection has attracted less research than edge detection. A simple model of a line would be two opposite edges connected by a uniform region. This might suggest that there is no need for a line detector since an edge detector in combination with some basic rules might work just as well (an example of such an approach can be found in [3]). However, this assumes a very simple model for a line which may not be sufficiently robust for general use.

Recently, several different approaches have been described for extracting the line information from (especially) mammographic images. In the remainder of this section five such approaches will be discussed all of which are in principle capable of extracting line strength, orientation and scale at a pixel level. The methods discussed are based on simple orientation bins, a directional line operator, directional second order Gaussian derivatives, directional morphology and curvi–linear structure detection.

These five methods are not an exhaustive set as other methods can be applied such as those based on flow fields [6] or on information in the local Fourier transform [7].

2.1 Orientated Bins

The Orientated Bins method is illustrated in Figure 1. The local neighborhood of the target pixel is divided into n angular bins (8 in this case) giving an angular resolution of $2\pi/n$. The choice of n involves a compromise between angular resolution and the reliability of line strength estimates. In Figure 1, only the pixels which fall between the two circles are taken into account. The resulting line strength is based on the number of pixels and their relative intensity which fall into a certain orientated bin. The relative intensity is determined by the total intensity of all the pixels per orientated bin divided by the number of pixels in those bins (which is necessary as no pixel weighting is applied). Line strength is given by the difference between the maximum relative bin intensity and the relative intensity of the whole neighborhood. The local line orientation is given by the bin with the maximum relative intensity. For a well defined line only two opposite bins would give a high response, while an area without a line structure present would give a more uniform distribution over the available bins. Line scale can be obtained by applying this method at multiple scales either by subsampling the image or changing the local area size. The local scale is taken as that which gives the highest line strength.

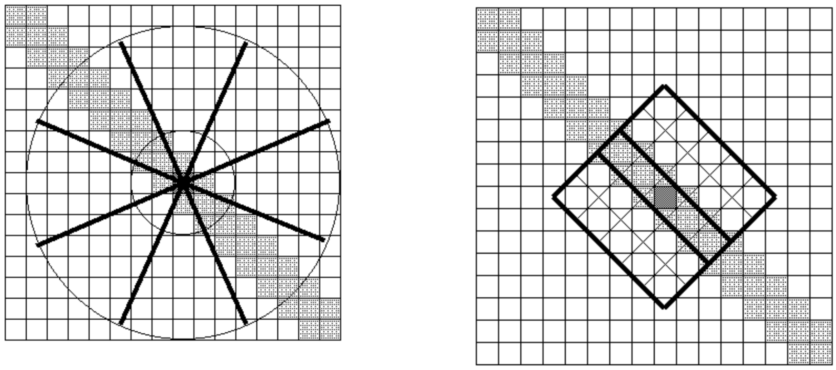

Figure 1. The local area in an image with a line and the operation of the Orientated Bins method (left) and the Line Operator (right).

2.2 Line Operator

The Line Operator [8] is based on a similar principle to the Orientated Bins approach and is illustrated in Figure 1. The Line Operator improves the line signal to background noise ratio by taking the average grey level of the pixels lying on an orientated local line passing through the target pixel and subtracting the average intensity of all the pixels in the locally orientated neighborhood. The values of pixels falling on the border of the line or neighborhood are weighted according to the area of the relevant pixel falling within the line or neighborhood. Pixels are assumed to be square.

The line strength is compared for n orientations. Line direction is obtained from the orientation producing the maximum line strength. Scale information can be obtained similarly to the orientated bins method. Different sized lines are detected by applying the Line Operator to images that are rescaled by Gaussian smoothing and subsampling. For each pixel, the scale producing the maximum line strength is taken as the detected line scale.

The speed of the Line Operator can be improved by precomputing the local line and neighborhood pixel positions and weights for each orientation and decomposing the Gaussian smoothing into one dimensional filters.

2.3 Directional Second Order Gaussian Derivatives

The method developed by Karssemeijer [5] is based on scale space. Directional second order Gaussian derivatives are used to find the orientation, strength and scale information of lines in images. The results of convolving the image with kernels at three different orientations are combined according to scale space theory [9] to give the orientation and line strength at a pixel level. The proper scale of lines is found by applying the derived methods for various widths of the Gaussian derivatives and finding the highest line strength response with respect to all the widths (which also indicates the line orientation). To save time the convolution can be performed in Fourier space.

2.4 Directional Morphology

Directional morphology can be used to detect line structure [10]. The detection of lines proceeds initially by application of a standard non–directional opening using a circular structuring element. The circle size is tuned to the maximum line width to be detected. The resulting coarse structure image is subtracted from the original image resulting in an image containing only fine scale structures. The method continues by application of a directional opening using an oblong structuring element that has a length and width tuned to the sizes of the lines to be detected. The opening is performed with the oblong orientated at n directions (typically with a resolution of $\pi/12$). The direction producing the highest response provides the line strength and orientation.

2.5 Curvi–Linear Structures

The curvi–linear structures method takes the local line profile into account to determine the line strength [11,12]. Line detection involves two stages. Candidate pixels for curvi–linear structures are detected using the response of a second difference operation which is applied in four directions. If there is a sufficiently high response for one of the orientations the pixel will form part of a curvi–linear structure. A measure of line strength is obtained by determining the contrast of the line profile at these pixels. It is not clear if the line orientation can be obtained easily since the four orientations of the second difference operation do not provide a high enough angular resolution. However, it might be possible to obtain a local orientation by taking an average of the orientation within every separate curvi–linear structure. The detection algorithm for the curvi–linear structures was provided by the Robotics Research Group at Oxford University. The single–scale results from this algorithm were used to obtain the line–strength images at a number of scales which were combined to produce a multi–scale result.

3 Line Detection Results

We have compared the performance of the five methods described above by applying them to synthetic images designed to test their application to digitised mammograms (see Figure 2). Linear structures were generated at known positions and orientations and with profiles which were generated by a model trained on spicules (the linear structures which radiate from stellate lesions) and blood vessels, both of which are linear structures found in mammograms [13]. The line patterns were superimposed on real mammogram backgrounds. Figures 2b and 2c show the patterns superimposed on dense and fatty backgrounds respectively. Notice should be taken of the fact that the original image, which is 426 pixels square, is superimposed on a larger area background (i.e. 512 pixels square).

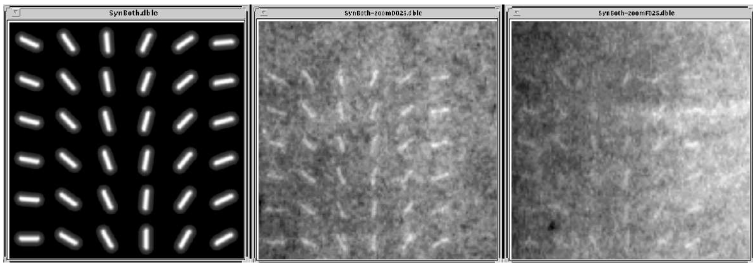

Figure 2. a.) Original artificial line image, and the same image superimposed on a b.) dense and c.) fatty mammographic background.

3.1 Line Strength

The line strength as obtained by the various methods can be compared with the true line strength. Figures 3a and 3b show results for line detection based on line strength, plotted as receiver operating characteristic (ROC) curves. For comparison we have included results which are based on a simple threshold.

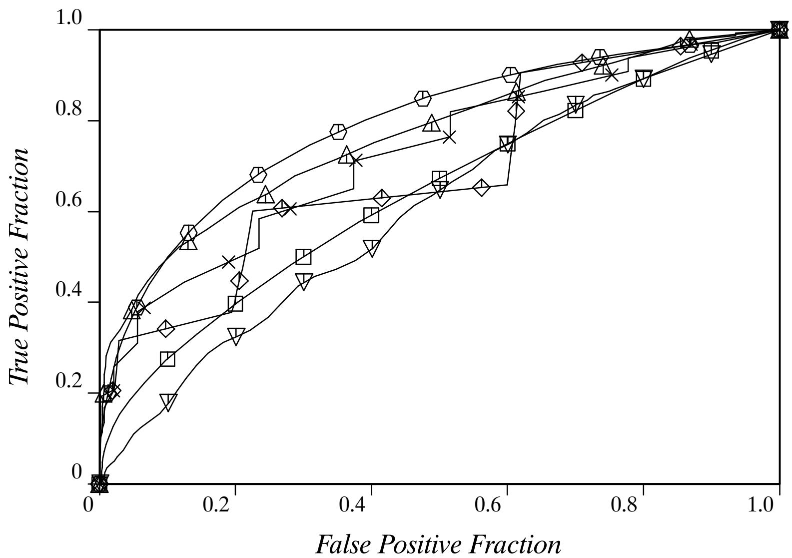

Figure 3a. ROC curves of the various line detectors for the artificial line image superimposed on the dense mammographic background were ⬡ : Orientated Bins, △ : Line Operator, □ : Directional Gaussian Derivatives, ◇ : Directional Morphology, ▽ : Curvi–Linear Structures and × : Simple Threshold.

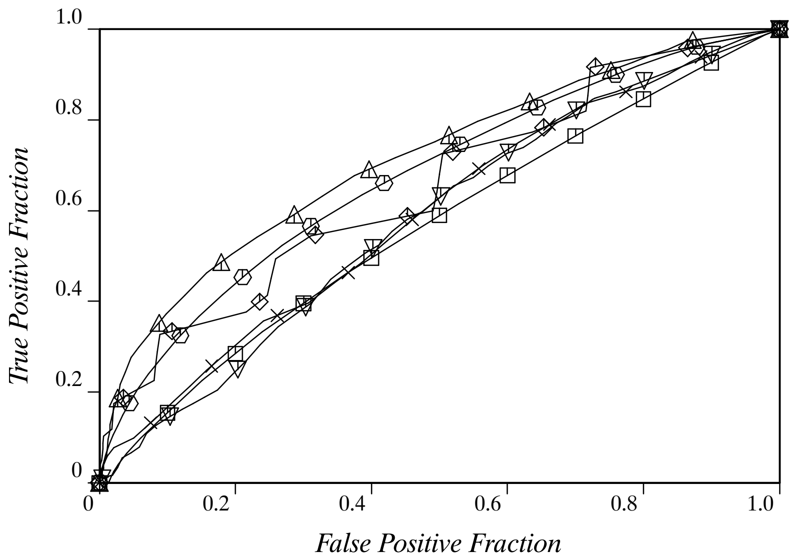

Figure 3b. ROC curve of the various line detectors for the artificial line image superimposed on the fatty mammographic background were ⬡ : Orientated Bins, △ : Line Operator, □ : Directional Gaussian Derivatives, ◇ : Directional Morphology, ▽ : Curvi–Linear Structures and × : Simple Threshold.

The ROC curves were obtained by varying a line–detection threshold and comparing the resulting pixel labels (line/not line) with ground truth. The closer a curve approaches the top left–hand corner the better the line detection.

These results suggest that the Line Operator and Orientated Bins methods perform best on both types of background, with the Directional Gaussian Derivatives and Curvi–Linear Structures methods performing least well and produce results which are worse or comparable with results based on a simple threshold. If an operating point is chosen where the proportion of false responses is reasonably low there can be a factor of two difference in the true positive detection rate between the best and worst methods. As expected the results for the fatty background are worse than those for the dense background.

3.2 Line Orientation

Besides the line strength the most important line information is provided by the local orientation. This can also be obtained at a pixel level for all the methods tested except for that based on Curvi–Linear Structures. For this comparison only the pixels on the backbone (highest intensity) of the lines were taken into consideration. With the exception of the Directional Second Order Gaussian Derivative approach all methods had an angular resolution of $\pi/12$. The results are shown in Figures 4a and 4b. The first point to note is that the overall orientation information is less reliable for the fatty background than for the dense background. The different methods are fairly comparable with slightly better performance for the method based on the orientated bins approach.

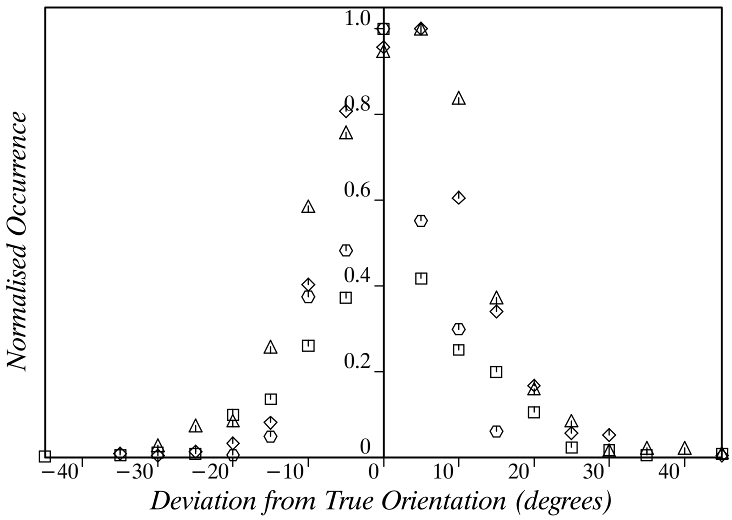

Figure 4a. Deviation from true orientation for the various line detectors with respect to the artificial line image superimposed on the dense mammographic background were ⬡ : Orientated Bins (σ=15.4), △ : Line Operator (σ=25.5), □ : Directional Gaussian Derivatives (σ=17.4), ◇ : Directional Morphology (σ=20.9).

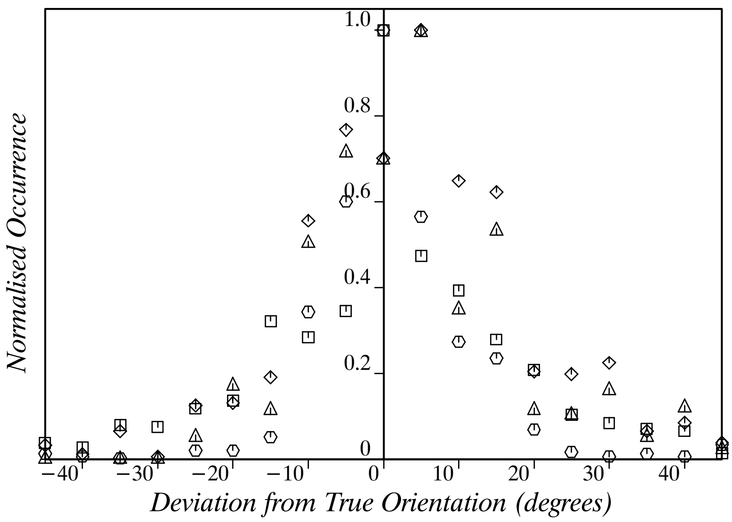

Figure 4b. Deviation from true orientation for various line detectors with respect to the artificial line image superimposed on the fatty mammographic background were ⬡ : Orientated Bins (σ=17.4), △ : Line Operator (σ=31.2), □ : Directional Gaussian Derivatives (σ=30.4), ◇ : Directional Morphology (σ=30.6).

4 Mammographic Images

In this section we show results for the most promising line detection methods applied to real mammographic images. Figure 5 shows the original of a section of a mammogram containing a stellate lesion. The original mammogram was obtained from the MIAS database (mdb181lm). It is clear that there is a radiating pattern of linear structures (with a central mass).

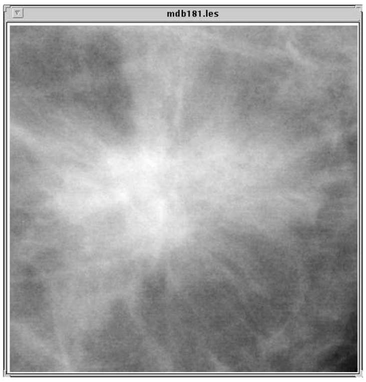

Figure 5. Part of a mammographic image containing a stellate lesion.

The main objective is to show how the orientation and line strength information behave with such an image. The line strength images are mapped to a grey level range of 0..255. The orientation images are mapped from 0 to π.

Figure 6 shows the line strength and orientation images obtained using the Orientated Bins approach at a single scale. A 32x32 local area was used with an angular resolution of $\pi/12$.

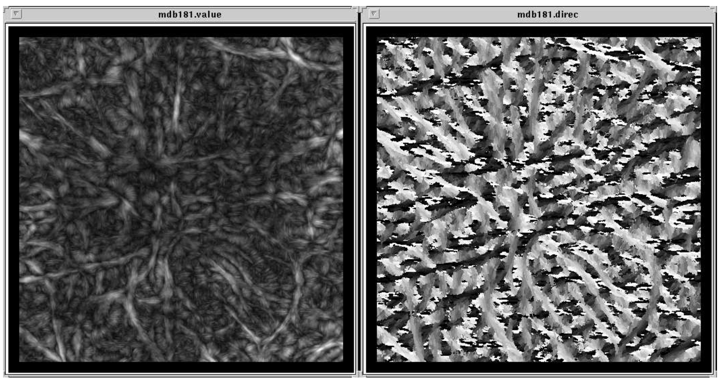

Figure 6. Line strength (left) and orientation (right) results from a single scale orientated bin approach.

Figure 7 shows the line strength and orientation images as obtained by using a multi scale Line Operator approach. The multi scale approach subsamples the original image and uses a small kernel (i.e. 5x5 pixels) and an angular resolution of $\pi/12$.

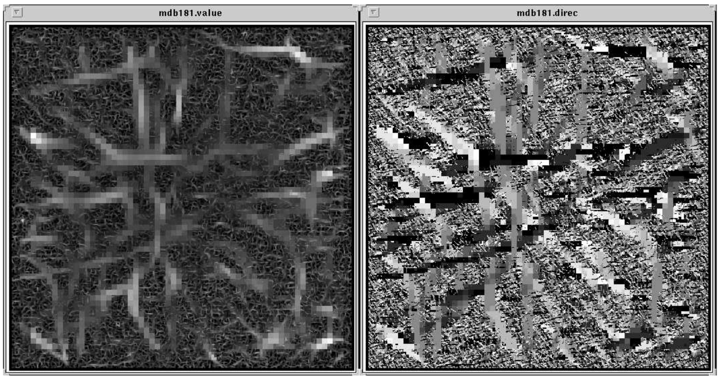

Figure 7. Line strength (left) and orientation (right) results from a multi scale line operator approach.

Both methods appear to recover structure and orientation satisfactorily, though the multi–scale approach shown in Figure 7 provides, as expected, a more complete description. For presentation purposes the line strength and orientation images can be displayed using colour space, where the line strength represents the saturation and the orientation the hue in colour space.

Once the line strength and orientation are found at a pixel level simple measures can be used to determine if a radiating pattern is present in the mammographic image. Such simple measures typically determine the number of pixels in a local region which are pointing towards the centre of that region and if how those pixels are distributed with respect to orientation [5].

5 Conclusions and Future Directions

We have compared the performance of several different approaches to the detection of linear structures in mammographic images. Results obtained using synthetic images suggest significant differences between the different approaches with the approaches based on the Orientated Bins method and the Line Operator method producing the best line strength results and the Orientated Bins method the best line orientation results. The most promising approach has been implemented as a multi–scale operator and gives intuitively convincing results. The output could be used directly in existing algorithms for classifying linear structures [13] and their spatial patterns [3–5]. We are currently investigating more principled methods of representing and classifying patterns of linear structures.

Acknowledgement

Funding from EPSRC under the PRISM project is gratefully acknowledged. We would like to thank Nico Karssemeijer for providing insight into the use of the Directional Second Order Gaussian Derivatives approach and Nick Cerneaz, Ralph Highnam and Paul Hayton for helping us to get their Curvi–Linear Structures detection code to run.

References

[1] Hutt, I.W., Astley, S.M. and Boggis, C.R.M., "Prompting as an aid to diagnosis in mammography", Excerpta Medica International Congress Series, **1069**, 1994, pp 389–398.

[2] Tabar, L. and Dean, P.B., *The Mammographic Teaching Atlas* Georg Thieme Verlag, Stuttgart, 1985.

[3] Kegelmeyer Jr., W.P., "Computer detection of stellate lesions in mammograms", SPIE, **1660**, 1992, pp 446–454.

[4] Astley, S.M., Taylor, C.J., Boggis, C.R.M., Asbury, D.L. and Wilson, M., "Cue generation and combination for mammographic screening", *Visual Search II*, (Brogan, Carr and Gale, Eds), Taylor and Francis, London, 1993, Chapter 13.

[5] Karssemeijer, N., "Detection of stellate distortions in mammograms using scale space operators", *Information Processing in Medical Imaging*, (Y Bizias et al. Eds), Kluwer Academic Publishers, Amsterdam, 1995, pp 335–346.

[6] Kass, M. and Witkin, A., "Analyzing oriented patterns", Computer Vision, Graphics, and Image Processing, **37**, 1987, pp 362–385.

[7] Zwiggelaar, R. and Bull, C.R., "On the use of local and scalable Fourier transforms, fractal dimension information, and texture segmentation", Proceedings of the Fifth International Conference on Image Processing and its Applications, Edinburgh, UK, 1995, pp 100–104.

[8] Dixon, R.N. and Taylor, C.J., "Automated asbestos fibre counting", Inst. Phys. Conf. Ser., **44**, 1979, pp 178–185.

[9] Koenderink, J.J. and van Doorn, A.J., "Generic neighborhood operators", IEEE Transactions on Pattern Analysis and Machine Intelligence, **14**, 1992, pp 597–605.

[10] Vincent, J., "Morphological grayscale reconstruction in image analysis: applications and efficient algorithms", IEEE Trans Image Processing, **2**, 1993, pp 176–201.

[11] Cerneaz, N. and Brady, M., "Finding curvi–linear structures in mammograms", Lecture Notes in Computer Science, **905**, 1995, pp 372–382.

[12] Steger, C., "Extracting curvi–linear structures: a differential geometric approach", Lecture Notes in Computer Science, **1064**, 1996, pp 630–641.

[13] Parr, T.C., Astley, S.M. and Boggis, C.R.M., "A model description of curvi–linear structures in digitised mammograms", Rontgen Centenery Congress, Birmingham, 1995, pp 123.