Texture Segmentation in Mammograms

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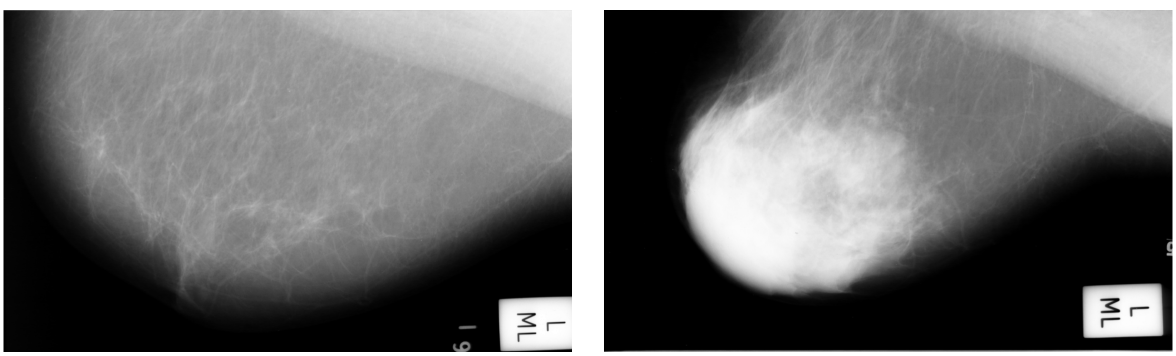
Abstract. We have investigated a combination of statistical modelling and expectation maximisation for a texture based approach to the segmentation of mammographic images. Texture modelling is based on the implicit incorporation of spatial information through the introduction of a set-permutation-occurrence matrix. Statistical modelling is used for dimensionality reduction, data generalisation and noise removal purposes. Expectation maximisation modelling of the resulting feature vector provides the basis for image segmentation. The developed segmentation results are used for automatic mammographic risk assessment.

1 Introduction

Texture is one of the least understood areas in computer vision and this lack of understanding is reflected in the ad-hoc approaches taken to date for texture based segmentation techniques. Although no generic texture model has emerged so far a number of problem specific approaches have been developed successfully [1]. Although the described approach is developed with one particular application in mind, we do believe that it is generic within the field of medical image understanding.

Since Wolfe's [2, 3] original investigation into the correlation between mammographic risk and the perceived breast density a number of automatic approaches have been developed [4–6]. Example mammograms are shown in Fig. 1. Some of these methods are based on grey-level distributions whilst others incorporate some aspect of spatial correlation or texture measure. While all these methods achieve some correlation with manual visual assessment in general they are not as good as expert intra-observer agreement. The accurate and robust estimation of mammographic density can be used for risk modelling and possibly to determine screening intervals within breast screening programmes.



(a) (b)

Figure 1. Fatty (a) and dense (b) mammographic images.

It is our thesis that the relative size of segmented image regions, representing distinct anatomical tissue classes, is correlated with mammographic risk assessment. Statistical modelling in combination with expectation maximisation (EM) [7] is used for the segmentation of mammographic images. To our knowledge, we introduce a new concept, the set-permutation-occurrence matrix, as a texture feature vector. Realistic texture modelling is possible as spatial information is implicitly incorporated. To achieve segmentation a number of steps are required: a) information gathering which transforms the original data in a multi-scale representation; b) texture feature extraction which uses the set-permutation-occurrence matrix concept to generate a feature vector at a pixel level; c) statistical modelling to provide a more compact and generalised representation of the data; d) EM clustering to divide the data in an optimal set of classes; and e) image segmentation which uses the classes for each pixel. The relative size of the segmented image regions is used, in combination with a nearest-neighbour classifier, to estimate the density for each mammogram.

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2 Methods

In general the usage of the EM approach [7] for image segmentation is based on the grey-level information at a pixel level with no direct interaction between adjacent pixels. However, it is well known that texture based segmentation should incorporate spatial correlation information. This means that our modelling should not be based on a single grey-level value but incorporates spatial information implicitly.

The first step in obtaining the texture features is the generation of an image-stack which is a scale-space representation. At the smallest scale the original grey-level values are used and to obtain the larger scale images we have used a recursive median filter [8], denoted $\otimes$, and a circular structuring element, R (the diameter of the structuring element increases with scale σ). The resulting image-stack is a set of images

$$\bigcup_{\sigma\in\Gamma}\{I_\sigma\} = \bigcup_{\sigma\in\Gamma}\{I \otimes R_\sigma\}, \tag{1}$$

where Γ is an ordered set of scales. This effectively represents a blurring of the original data and at a particular level in the image-stack only features larger than σ can be found. An alternative representation of the image-stack is given by

$$\bigcup_{\sigma\in\Gamma}\{\overline{I}_\sigma\} = \bigcup_{\sigma\in\Gamma}\{I \otimes R_{\sigma-1} - I \otimes R_\sigma\}, \tag{2}$$

where Γ is a set of scales. This represents the differences between two scales in I_σ and hence the data in the image-stack at a particular level will only contain features at a particular scale σ. It should be made clear that the representation given by Eq. 2 does not result in a gradient image.

To capture the texture information over a set of scales a feature vector will need to be extracted from the image-stack. Small size aspects (like noise and small objects) are represented at the top (least amount of smoothing) of the image-stack. On the other hand, large size aspects (large and background objects) are represented at the bottom (after smoothing at the appropriate scale) of the image-stack.

The developed method uses a model that can be seen as a generalisation of normal co-occurrence matrices [9]. Indeed, if we just look at the co-occurrence of grey-level values the information can be captured in matrix format, where the rows and columns represent the grey-level values at two sample points. This process can include a set of points S_{xy}. An example of the points used is shown in Fig. 2. In the experiments described below we have used

$$S_{xy} = \bigcup_{\varepsilon\in D}\big\{(x, y+\varepsilon), (x+\varepsilon, y)\big\} \tag{3}$$

where $D = \{-32, -16, -8, -4, -2, 0, 2, 4, 8, 16, 32\}$. In the case described here we generate the co-occurrence between all the points in the set of sample points; i.e. a permutation of all points in the set. This is illustrated in Fig. 3 for one particular point, but it should be noted that the same approach is used in a round-robin way or in other words the points are fully connected. When using $\{\overline{I}_\sigma\}$ (a similar notation can be obtained when using $\{I_\sigma\}$), this representation of the texture information in the form of a matrix is given by

$$\overline{\mathbf{\Psi}}^\sigma(x, y) = \left[\psi^\sigma_{i,j}\right]_{i,j\in N_g} \tag{4}$$

and

$$\psi^\sigma_{i,j} = \#\big\{(p, p') \in S_{xy} \times S_{xy} \mid \overline{I}_\sigma(p) = i,\ \overline{I}_\sigma(p') = j\big\} \tag{5}$$

where $\#$ denotes the number of elements in a set and N_g denotes the set of grey-level values. It should be noted that this approach provides a different description than that would be provided by using a set of co-occurrence matrices.

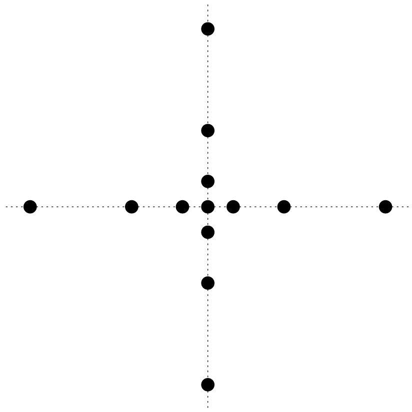

Figure 2. Sample points S_{xy}.

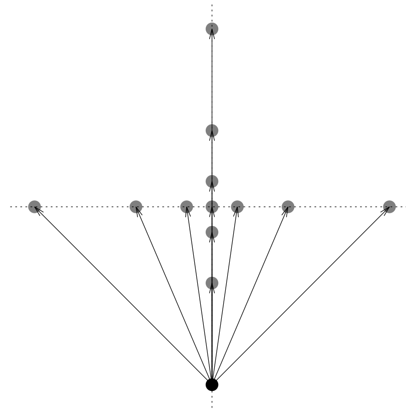

Figure 3. Sample points connectivity.

Instead of using the co-occurrence of the grey-level values it is possible to use the occurrence of the grey-level difference. Again, this is using the same set of sample points S_{xy} (see Figs 2 and 3) at each scale (i.e. level in the image-stack). As we are using the occurrence of the grey-level difference values our grey-level co-occurrence matrix reduces to a vector. Effectively this is an alignment of the columns of the co-occurrence matrix with respect to the diagonal (i.e. where the difference in grey-level values is equal to zero) and a subsequent summation over the rows. When using the difference image-stack representation (see Eq. 2) the feature vector at a single scale is given by

$$\overline{\Phi}^{\sigma}(x,y) = \left[\phi_i^{\sigma}\right]_{i \in \delta_{N_g}} \tag{6}$$

where N_g is the set of grey-levels, σ a given scale, δ_{N_g} is the set of grey-level differences and

$$\phi_i^{\sigma} = \#\left\{(p,p') \in S_{xy} \times S_{xy} \mid \overline{I}_{\sigma}(p) - \overline{I}_{\sigma}(p') = i\right\} \tag{7}$$

where, again, $\#$ denotes the number of elements in a set.

The texture feature described above is extracted at a pixel level and combining the texture features over all possible scales results in a feature vector. We have used principal component analysis [10] to provide a more compact representation of the feature vector.

3 Results

The EM approach [7] is used to determine a set of classes from the feature vectors which can be used to segment the images. Although of interest, it is computationally impractical to base the EM modelling on the original texture feature vector as this has a large number of elements (a high dimensionality) and tends to be sparse. All the results presented in this section are based on a PCA reduced feature vector where we typically capture 95% of the data variation (the dimensionality of the data was approximately reduced by a factor of ten). The EM and statistical modelling process take only the breast area into account whilst excluding the pectoral muscle and the background. For the EM approach the number of classes was set equal to six [11].

To test our thesis that the relative size of the segmented regions is linked to mammographic risk a small subset of the Mammographic Images Analysis Society (MIAS) database was used [12, 13]. All the images were assessed by mammographic experts who provided an estimate of the proportion of dense tissue in each mammogram. The segmentation results, based on EM and statistical modelling using $\{I_{\sigma}\}$ or $\{\overline{I}_{\sigma}\}$, can also be used to obtain the relative size of the segmented regions for each class. This feature is used as our classification space. The correlation between the relative region size distribution and the estimated proportion of dense tissue, when using a nearest neighbour classifier on a leave-one-out basis for $\{\overline{I}_\sigma\}$, can be found in Table 1. This shows an agreement for 86% of the mammograms (this decreases to 66% when using $\{I_\sigma\}$. This compares well with an inter-observer agreement of 45%. The intra-observer agreement on the used dataset is 89%. In addition, when using the same data set and classification approach, results based on the approaches developed by Byng [5] and Karssemeijer [4] show an agreement of 67% and 81%, respectively.

		Expert Classification			
		0-10%	11-25%	26-50%	51-75%
Automatic Classification	0-10%	6	0	0	0
	11-25%	0	5	2	0
	26-50%	2	1	8	0
	51-75%	0	0	0	12

Table 1. Comparison of the density estimate as given by an expert radiologist and automatic segmentation. Based on $\{\overline{I}_\sigma\}$.

4 Conclusions

We have shown that a combination of EM and statistical modelling results in a robust approach to the segmentation of mammographic images. We have introduced a texture feature vector based on a set-permutation-occurrence matrix which captures both spatial and local grey-level information. The use of this type of matrix will need further development to explore its limitations and full potential. It should be noted that some fundamental questions, such as the influence of the size and shape of the distribution of sample points S_{xy}, need further investigation. In addition, the developed texture segmentation approach will be fully evaluated on synthetic and natural textures.

We have shown that the segmentation results can be used to provide valuable information in the estimation of mammographic density and therefor possibly for mammographic risk assessment. The developed approach is comparable to expert intra-observer variation, shows considerable improvement on the inter-observer agreement and compares favourable with existing techniques.

Acknowledgement

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