Textural Analysis Optimisation in MRI of the Breast

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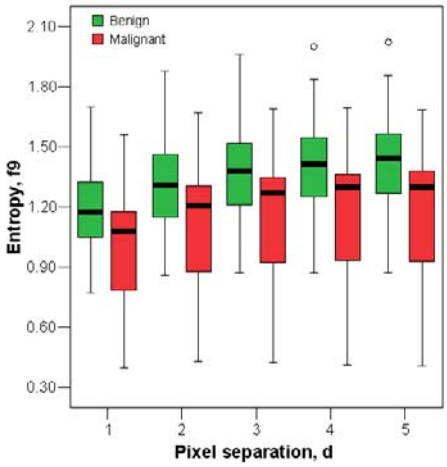
Introduction Quantitative textural analysis is an established method of image classification in aerial and satellite photography. In recent years attempts have been made to utilise texture in MRI, particularly in the brain [1-6], but also in other organs such as breast [7] and liver [8]. One of the commonest methods of analysis, the spatial gray-level dependence matrices (SGLDM) technique proposed by Haralick *et al* [9], has been found to provide as much discriminatory power as other procedures [10]. Calculation of textural parameters using SGLDM relies on the initial construction of co-occurrence matrices which detail the joint probability of two pixels a specified distance *d* apart having co-occurring values *i* and *j*. The optimal value for *d* is unknown. Small values of *d* imply classification of fine textural features whereas coarser features require higher values of *d*. MR images are typically acquired with 12 – 16 bit accuracy theoretically spanning 4096 – 65536 gray-levels. In practice, to avoid the potential for over-ranging, acquired data spans approximately 10 bits or 1024 gray-levels that, without modification, results in a co-occurrence matrix containing over a million elements. Anatomical and pathological regions within the image clearly contain far fewer pixels (at least 2 orders of magnitude) leading to extremely poor counting statistics. It is usual, therefore, to reduce the number of gray-levels present in the image prior to textural analysis. The appropriate level of reduction is unclear, since improved counting statistics undoubtedly result but potentially at the expense of discriminatory power. This work attempts to explore textural analysis parameter optimisation in MRI of the breast.

Methods Data from 47 patients (25 benign and 25 malignant lesions) was retrospectively analysed. All images were acquired using a 1.5 T GE Signa Echo-speed scanner with the patient prone and the breasts suspended in a dedicated breast coil. After dynamic contrast-enhanced imaging, high-resolution, fat-suppressed, post-contrast images were obtained using a fast spoiled gradient-recalled-echo (FSPGR) sequence (TR/TE 23-28/4.2 ms, flip angle 30°, field of view 20×20 cm, matrix size 512×256, slice thickness 3-5 mm, 1 average). After acquisition an experienced radiologist examined and drew ROIs encompassing the whole lesion as closely as possible whilst excluding spiculations and surrounding fat. Co-occurrence matrices and subsequent textural parameters were calculated for data reduced to 4, 5, and 6-bits (16 – 64 gray-levels) at pixel separations of 1, 2, 3, 4, and 5 using MaZda software [12]. Only the first 11 (out of 14) textural parameters defined by Haralick *et al* [9] were available using this software. Differences between benign and malignant lesions were evaluated using the independent samples *t*-test or non-parametric equivalent where appropriate.

Results For a pixel separation, *d*=1, the same 8, out of 11, textural parameters demonstrated significant differences between benign and malignant lesions when data was reduced to 64 ($p < 0.032$) or 16 ($p < 0.028$) gray-levels (see table for details). Conversely, when data was reduced to 32 gray-levels only 1 parameter out of 11 (f_1, $p = 0.042$) showed a significant difference between the two groups. Adjusting the pixel separation, *d* for 64 gray-level data revealed no obvious variations in the number of significant parameters obtained. Similar results were obtained for 32 and 16 gray-level data. The boxplot below illustrates the variation in f9, entropy (a measure of disorder) with pixel separation for the 16 gray-level data. Whilst there is a slight increase in median values from 1 to 3 pixels there is no improvement or concomitant deteriation in the overlap between the two groups.

Textural Parameter	*64-gray levels*	*32 gray-levels*	*16 gray-levels*
f_1-ASM	*0.016*	*0.042*	*0.013*
f_2-Contrast	0.078	0.575	0.092
f_3-Correlation	0.639	0.515	0.225
f_4-Variance	*0.014*	0.530	*0.022*
f_5-IDM	*0.003*	0.190	*0.012*
f_6-Sum Average	*0.030*	0.977	*0.028*
f_7-Sum Variance	*0.014*	0.535	*0.022*
f_8-Sum Entropy	*0.027*	0.408	*0.011*
f_9-Entropy	*0.032*	0.400	*0.013*
f_{10}-Difference Variance	0.097	0.453	0.115
f_{11}-Difference Entropy	*0.010*	0.439	*0.026*

P-value variation with number of gray-levels (Significant differences are shown in italic)



Discussion The insensitivity to pixel separation reported herein seems to indicate that fine and coarse textural features are present, within both benign and malignant lesions, to a similar extent. From the table it is evident that there is a discrepancy at 32 gray-levels. Tozer *et al* reported reasonably consistent p-values over a wide range of gray-level reductions. However, their work was confined to the brain, with associated higher SNR, and did not investigate data reduction below 32-gray levels. The results obtained in this work may be peculiar to this particular dataset and as such warrant further investigation on a larger number of lesions.

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