Textural Analysis of DCE-MRI of the Breast as a Predictor of Response

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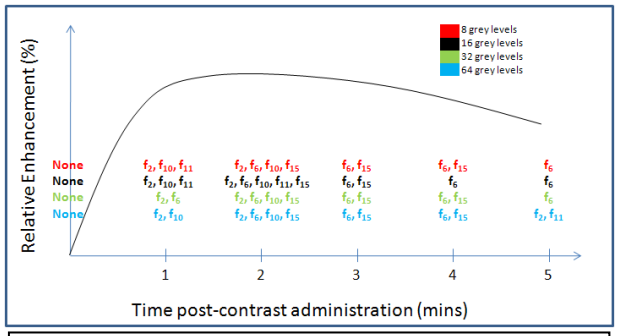
Introduction Textural analysis is an established method of image classification in aerial and satellite photography. Recently, attempts have been made to utilise texture in MRI, particularly in the brain [1-3], but also in other organs such as the breast [4] wherein lesion morphology is known to be an important diagnostic and prognostic indicator [5]. Whilst previous research has generally concentrated on quantifying morphology in high resolution data there appears to be some value in assessing lesion texture in dynamic contrast-enhanced (DCE) images [6], especially with regards to changes during the initial enhancement and subsequent washout phases. The spatial gray-level dependence matrix method, as proposed by Haralick [7], appears to be the commonest form of analysis, but there is no direct evidence concerning the most appropriate pixel separation and number of grey levels to utilise in the required co-occurrence matrix calculations. This works aims to systematically assess the efficacy of DCE-MRI based textural analysis in predicting response to chemotherapy in a cohort of breast cancer patients.

Methods 100 patients were scanned on a 3.0T HDx scanner immediately prior to neo-adjuvant chemotherapy treatment. For all patients a 3D dynamic dataset was acquired using VIBRANT (FOV 20×20 cm, acquisition matrix 220×160, slice thickness 2 mm, 12 phases with average tdel=33.7 s, range 25.5-44.7 s) Malignant tissue ROIs were generated semi-automatically on all slices utilising early arterial phase data. Texture analysis was then performed on pre-contrast and 1, 2, 3, 4 and 5 minutes post-contrast data. To prevent sparseness within subsequently calculated co-occurrence matrices the ROI data underwent grey level decimation via histogram equalisation. ROI data was reduced to 8, 16, 32 and 64 grey levels since the optimal number is unknown (reducing the number of grey levels improves SNR at the expense of discriminatory power).

Co-occurrence matrices, which contain the joint probability of two adjacent pixels along a given direction θ having co-occurring values i and j, were calculated for θ = 0°, 45°, 90° and 135° and subsequently averaged. The 14 textural features as defined by Haralick (denoted f_1 to f_{14} and including entropy, angular second moment and correlation) were then determined alongside two further parameters cluster shade (f_{15}) and cluster prominence (f_{16}) [8]. Patient groups were determined based on nodal status and response. Differences between groups were investigated using simple *t*-tests or the non-parametric equivalent where appropriate.

Results Nodal status was determined in 91 patients (45 node –ve vs. 46 node +ve) and response data was available in 89 patients (40 partial responders vs. 49 non-responders). Regarding nodal status significant differences in f_6 (sum average) and f_{15} were noted at 2, 3 and 4 minutes post-contrast administration for all grey level choices. Differences were noted between partial responders and non-responders for f_2 (contrast) and f_{10} (difference variance) at 1 and 2 minutes post-contrast administration. Interestingly, no significant differences were found pre-contrast administration. The results are summarised in the figure alongside highlighting the best discrimination between groups at 2 minutes post-contrast.



Significant texture parameters colour coded according to number of grey levels used in co-occurrence matrix calculation

Discussion This work has highlighted that textural differences between groups (based on response or nodal status) are apparent and appear to be most evident 2 minutes post-contrast administration. Whilst the large number of statistical tests undertaken necessitates a degree of caution in interpreting the results, the fact that significant differences, in f_6 and f_{15} for nodal status, and f_2 and f_{10} for response, are consistently observed is encouraging. Future work will concentrate on assessing texture differences with regard to other prognostic indicators and on utilising principal component analysis to reduce the dimensionality of this large dataset.

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