The effect of acquisition parameter changes on the outcome of texture analysis using a clinical breast MRI sequence on a foam phantom at 1.5T

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Introduction and Aims: The texture present in medical images can be described as relating to the distribution of different pixel intensities and can be used for the visual identification of different tissue types. A wealth of information is contained within finer digital texture that is not perceived by the naked eye and can be extracted by computer analysis. Computer-based texture analysis uses statistical models to extract this information, and it has been used with medical imaging modalities such as magnetic resonance imaging (MRI) [1]. Breast MRI has been one of the areas to benefit from texture analysis, in which it has demonstrated an ability to increase the specificity of the examination [2].

It has been reported that texture analysis results are not consistent between different MRI scanners, e.g., due to differences in acquisition techniques and processing steps, and it has also been suggested that the signal to noise ratio (SNR) may affect the outcome of texture analysis [1, 3]. For MRI, this suggests that texture analysis may be dependent on sequence acquisition parameters.

The aim of this study was to evaluate - as part of the preliminary work up ahead of a patient study - the effects of changing parameters in a standard clinical breast MR sequence on the outcome of texture analysis. These were investigated in a breast phantom, as well as the ability of texture analysis to differentiate between four grades of foam.

Methods: A breast-mimicking phantom was constructed using lard as a fat substitute and gadolinium-doped agarose gel to represent fibroglandular tissue (T_1 and T_2 parameters were matched to those obtained clinically). Four different grades of reticulated foam were used as texture phantoms- 90, 75, 45 and 30 pores per inch (ppi) (Foam Engineers Ltd.; Buckinghamshire). These were embedded in the agarose and repeated compression was used to eliminate air bubbles trapped in the foam. The phantom was imaged on a 1.5 Tesla MRI scanner (Avanto; Siemens, Erlangen) using a 4-channel breast matrix coil. The routine 3D FLASH dynamic sequence from the breast imaging protocol was used, with parameters TR/TE= 3.8/1.24 ms, α=6º, FoV=320×320mm, Slice thickness= 0.83mm, Matrix= 384×384, Bandwidth= 650 Hz/px, parallel imaging factor of 2.

The phantom was imaged using the standard sequence, and then sequence parameters were changed in turn to identify the impact of these changes on texture analysis outcome. Three different parameters were considered: repetition time (TR), bandwidth/echo time (BW/TE) and flip angle (α). The bandwidth and echo time were linked together by minimising the TE for a given BW, as per the manufacturer's recommended protocol. Five different values were used for each sequence parameter, as shown in Table 1. In each case only one parameter was changed at any given time, and TR1, BW1 and α1 represent the baseline values.

TR (ms)		BW/TE (Hz/px /ms)		α (º)	
TR1	3.8	BW1	650/1.25	α1	6
TR2	4.0	BW2	590/1.26	α2	5
TR3	4.25	BW3	540/1.29	α3	4
TR4	4.5	BW4	500/1.31	α4	3
TR5	4.75	BW5	470/1.34	α5	2

Table 1- *Sequence parameter changes*

Texture analysis was carried out using MaZda version 4.7 [4] Circular regions of interest of no less than 300 pixels were placed in each of the four foam phantoms, across the ten central slices. Grey level normalisation was carried out by rescaling histogram data to fit within μ±3σ (μ-grey level mean, σ-grey level standard deviation) in order to minimise the effect of image brightness and contrast on the outcome of texture analysis. Texture features were then calculated using the auto-regressive model (ARM), co-occurrence matrix (COM), absolute gradient (GRA), run-length matrix (RLM) and wavelet transform (WAV) methods.

Feature classification was carried out using B11 software, version 3.3 [4]. As this accepts a maximum of 30 input texture features, the COM features were restricted by choosing an interpixel distance of one (to best reflect fine features) and two arbitrarily chosen directions of 0º and 45º. Linear discriminant analysis (LDA) was used to reduce datasets by calculating the most discriminating features, and classification was then carried out using the nearest neighbour technique (k-NN) with k=1. Incorrectly identified data was represented by the percentage of misclassified vectors.

In the first part of the experiment, texture analysis was performed to determine whether each model could accurately differentiate between each foam phantom for each sequence parameter indicated in Table 1. In the second part, it was investigated whether two image sets of the foam phantoms, each one acquired with different imaging parameters, could be differentiated from one another using texture analysis.

Results and Discussion: Each dataset consisted of 40 data points (4 foam porosities across 10 imaging slices) and a total of 13 datasets (baseline plus 4 parameter changes) were analysed for each texture model (five times). Results are presented in Table 2 as the average percentage misclassification for each group of five sequence parameter changes, after LDA and k-NN analysis. Discrimination between the four foam phantoms was perfect for all sequence parameters using the WAV method (0% data misclassification), and moderately so for COM parameters. GRA and ARM resulted in particularly poor classification (on average more than 50% data misclassification).

	ARM	COM	GRA	RLM	WAV
TR	60.5	12.5	64.0	39.0	0.0
BW	49.5	9.5	58.0	31.0	0.0
α	50.5	9.5	55.0	32.0	0.0

Table 2- *Average percentage of misclassified vectors for each model at each sequence parameter*

Comparison was then made between images acquired with different sequence parameters, and the ability of texture analysis to differentiate between two images was evaluated. Results are presented in Table 3 for the COM and WAV models as these proved to be the best methods for differentiating the various foams. The high rate of misclassification across all sequence parameter changes for COM features suggests that there were no detectable differences and therefore that sequence parameters had little influence on the outcome of texture analysis using this method. There were high rates of misclassification for the wavelet transform model for both the TR and BW experiments. It appears that flip angle may have had an influence on the outcome of texture analysis due to the low rate of misclassification. It should be noted, however, that a flip angle of 2º is unlikely to be used clinically and that the higher degree of noise may form some kind of 'structure' that is then detectable with texture analysis.

	COM	WAV
TR1 vs TR2	35.00	21.25
TR1 vs TR3	40.00	18.75
TR1 vs TR4	28.75	12.50
TR1 vs TR5	33.75	30.00
BW1 va BW2	42.50	26.25
BW1 vs BW3	25.00	30.00
BW1 vs BW4	21.25	33.75
BW1 vs BW5	26.25	25.00
α1 vs α2	38.75	13.75
α1 vs α3	33.75	12.50
α1 vs α4	32.50	5.00
α1 vs α5	22.50	0.00

Table 3- *Percentage of misclassified vectors when comparing texture analysis of two images acquired with different sequence parameters*

There appeared to be no systematic pattern to the rates of misclassification and no apparent influence of the signal to noise ratio on the outcome of texture analysis. We would expect higher rates of misclassification in lower SNR images, however there was no identifiable correlation between these parameters (r^2=0.024).

Conclusions: Digital texture analysis has been demonstrated to be able to reliably differentiate between four grades of foam in a breast-simulating phantom, despite the MR images appearing visually identical. The wavelet transform model resulted in perfect classification every time, and the co-occurrence matrix also performed reasonably well. Sequence parameter changes appeared to have little effect on the outcome of texture analysis using this particular protocol, which is in agreement with previous findings with spin echo sequences at clinical resolutions [5].

References

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