Texture Analysis Shows Abnormalities in White and Grey Matter T1 Maps in Multiple Sclerosis

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Introduction: Histogram and region of interest analysis of T_1 in normal appearing tissue are an effective tool for the classification of multiple sclerosis (MS) patients and controls (1). However, discrimination is not complete. One possible reason for this is that histograms take information from throughout an area and any local information is lost, whereas region of interest analysis requires choice of a small region, which limits the information used. Texture analysis allows local information to be retained by extracting parameters such as entropy and contrast from a large region. The commonly used parameters are the 14 defined by Haralick (2), which are extracted from the grey level (GL) co-occurrence matrix constructed from the data. Recent work (3) has suggested that images should be reduced in number of GL to reduce the sparsity of the matrices; this may however lose some of the information in the data. The sparsity of the co-occurrence matrix depends on region size, so the optimum number of GL will also be a function of this. This work investigates T_1 maps in MS patients and controls using texture analysis and the effect GL decimation.

Methods: T_1 maps were acquired from 14 controls and 23 relapsing remitting MS patients (mean EDSS (range) 1.1 (0-2.5)) using the method in (4). T_1 and PD weighted images were acquired and combined with a non-uniformity correction to produce a series of 28 5mm thick T_1 maps covering the whole brain with pixel size 0.94 by 0.94 mm. The PD images were segmented using SPM2 (Wellcome Department of Imaging Neuroscience, UCL, UK) and white and grey matter T_1 maps (WM and GM) produced. Partial volume pixels were eroded and upper thresholds of 1000 ms and 1700 ms were applied to the WM and GM maps respectively. The maps were reduced, including histogram equalisation, to 32, 64, 128, 256 and 512 GL, as well as the original 1000 for WM and 1024 and the original 1700 for GM. The GL co-occurrence matrix was then constructed for each map at each number of GL, using the 8 nearest neighbours, and the 14 texture analysis measures (2) calculated. The independent samples Students t-test was then used to test for differences in the parameters between the groups and a logistic regression used to asses their discriminatory power.

Results: The p-values for each texture parameter at each number of GL are shown in table 1. The results show that there are significant differences between the patients and controls for both white and grey matter. For WM it appears that the sum variance is the best discriminator and for GM the variance and sum average measures do best, although this does depend on the level of reduction used. There is also much consistency with regard to the significant parameters as the number of GL varies, although the texture parameters from the original maps do appear to follow a slightly different pattern to the reduced maps. For WM the logistic regression (using all significant and borderline significant texture parameters) results varied from 87% (64 and 128 GL) to 78% (512); for GM the range was 76% (512) to 65% (1700).

Discussion: The differences seen between the two groups using texture analysis suggests that small local changes, such as microscopic lesions, are occurring throughout the apparently normal tissues in patients. While the results are not highly significant, the logistic regression models produced classification rates of 83% and 70% for WM and GM respectively (averaged across all numbers of GL) which compare very well to other parameters (5) and are good considering the patients have a relatively low EDSS indicating little clinical impairment. It would appear that GL reduction has an effect on the texture parameters. This is most obvious in GM where the original 1700 GL produce the worst results in separating the groups, for WM any effect is less obvious although using 1000 GL had an 81% classification rate, only greater than 512 GL. This is most likely to be due to sparsity in the co-occurrence matrix with a large number of GL and shows that even with large whole tissue regions, GL reduction may still be needed. Once the GL are reduced the parameters seem to be independent of further reduction. This can be seen from table 1 and the fact that there is little difference in the logistic regression results, which are not correlated with the number of GL. There does not appear to be significant information loss associated with a dramatic reduction in GL, indicating that it may be better to over reduce, than under.

Conclusions: 1) Changes in both WM and GM in MS patients 2) Classification rates of up to 87% and 76%
3) Grey level reduction appears to improve classification 4) Little penalty for over reduction of grey levels

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	White Matter						Grey Matter						
Texture Parameter	32	64	128	256	512	1000	32	64	128	256	512	1024	1700
ASM*	0.458	0.371	0.761	0.627	0.722	0.671	0.680	0.768	0.686	0.347	0.174	**0.025**	*0.061*
Contrast	*0.074*	*0.077*	*0.074*	*0.077*	0.114	**0.034**	0.375	0.379	0.371	0.379	0.406	0.404	0.471
Correlation	0.162	0.427	0.143	0.407	0.307	0.529	0.554	0.150	0.245	**0.027**	**0.032**	*0.099*	*0.077*
Variance	0.903	0.903	0.908	0.919	0.937	0.779	**0.041**	**0.035**	**0.037**	**0.035**	**0.043**	**0.043**	0.133
IDM+	0.996	0.569	0.306	0.172	0.250	**0.041**	0.602	0.603	0.609	0.603	0.586	0.467	0.167
Sum Average	0.691	0.671	0.696	0.673	0.696	0.800	**0.042**	**0.038**	**0.038**	**0.037**	**0.046**	**0.045**	0.148
Sum Variance	**0.038**	**0.037**	**0.042**	**0.035**	**0.049**	0.339	0.989	0.972	0.992	0.969	0.986	0.976	0.805
Sum Entropy	**0.011**	**0.027**	0.560	0.238	0.329	0.100	0.892	0.682	0.703	0.690	0.821	0.937	0.788
Entropy	0.819	0.812	0.352	0.129	0.121	0.228	0.477	0.436	0.353	*0.053*	**0.047**	0.124	0.336
Diff. Variance$	*0.074*	*0.077*	*0.074*	*0.077*	0.114	**0.034**	0.374	0.378	0.371	0.377	0.406	0.404	0.471
Diff. Entropy$	*0.099*	0.120	0.127	0.136	0.188	*0.051*	0.477	0.480	0.478	0.485	0.512	0.514	0.455
Measure of Correlation 1	0.686	0.687	0.420	0.170	0.137	0.110	0.516	0.527	0.552	0.589	0.869	0.594	0.786
Measure of Correlation 2	0.626	0.635	0.469	0.127	0.110	0.105	0.488	0.502	0.527	0.593	0.821	0.565	0.676
Max. Correlation Coefficient	0.165	0.135	0.203	0.377	0.098	0.325	0.503	0.571	0.578	0.605	0.826	0.765	0.291

Table 1: p-values from comparisons of patients and controls for Wm and GM at each number of GL (2nd row). Significant differences ($p \leq 0.05$) are shown in **bold** and borderline differences ($0.1 > p > 0.05$) are shown in *italics*. *angular second moment, +inverse difference moment and $difference.