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CHARACTERIZATION OF MRI BRAIN SCANS ASSOCIATED TO ALZHEIMER'S DISEASE THROUGH TEXTURE ANALYSIS

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Abstract
The purpose of this project is to investigate datasets of T1-weighted MRI brain scans, aiming at discriminating normal from cognitive impaired patients, by describing the white/gray matter (WM/GM) image intensity variation in terms of textural descriptors from gray level co-occurrence matrices (GLCM). These descriptors form the feature vectors considered for later classification using non-supervised algorithms as k-means. We use MRI data sets from Open Access Series of Imaging Studies (OASIS), made available by the Washington University Alzheimer's Disease Research Center, HHMI, NRG and BIRN. Experimental results indicate that textural descriptors have potential to differentiate normal WM images from dementia-related WM images.

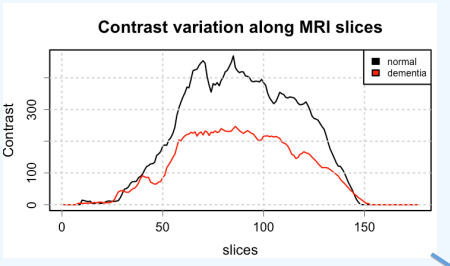
Methods
First, the WM/GM is isolated using spatial proximity of voxels to constrain the probability with which voxels of a given intensity are assigned to WM/GM (segmentation). Second, we determine sub-regions in each slice that contains only WM/GM intensities (masking), which are input to a statistical method for extracting the spatial organization of gray tones in MRI scans. Our study considers textural descriptors derived from the isotropic gray level co-occurrence matrix: contrast, correlation, energy and homogeneity for different distances *d*. The image processing and analysis uses ImageJ, Matlab and R tools, including a new plugin for calculating isotropic GLCM from specified regions of interest. Classification considers Clinical Dementia Rating (CRD)

Results
- Statistical texture descriptors that convey the spatial organization of gray tones, given two parameters: d={1,2,4,10} and angles α=0, 45, 90, 135 in MRI scans;
- For each cross-section of either WM or GM portions, we compute 4 textural descriptors. Each MRI volume is represented by the average and standard deviation of the textural descriptors for each portion at a certain *d*;
- Synthesis: raw measurements of texture as well as PCA of the scaled (variance fixed) variables, particularly the components carrying more than 90% of information;
- Individuals with CDR=2 will present MRI volumes characterized by a higher contrast, and larger variability across the scan slices than those with CDR<2.

Table 1. MRI Acquisition Details

Sequence	MP-RAGE
Magnetization (T)	1.5
TR (msec)	9.7
TE (msec)	4.0
Flip angle (°)	10
TI (msec)	20
TD (msec)	200
Thickness, gap (mm)	1.025, 0
Slice number	128
Resolution (pixels)	256 x 256 (1x1 mm)

*Based on table from Marcus et al. [1]



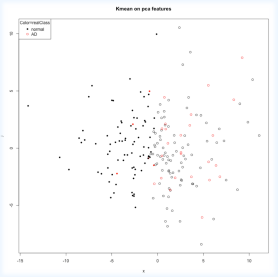
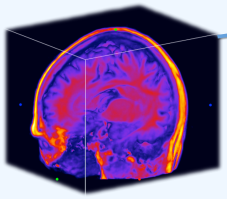
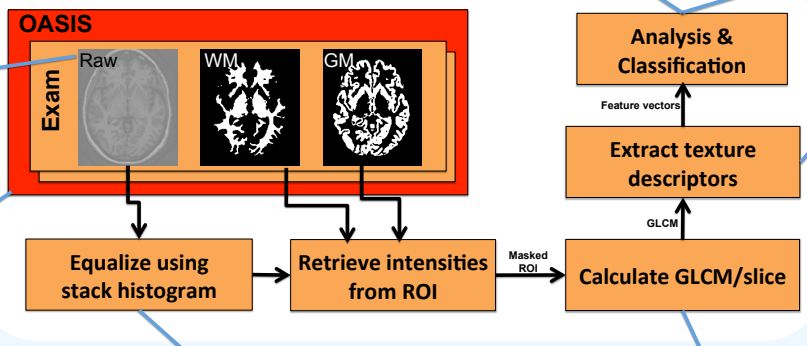


Figure 2. Classification results using k-means on PCA-based features for all the patients with age ≥ 60; color represents the real class while the symbol shows the predicted class.





$$Inertia = \sum_{i,j=0}^{n-1} p_{i,j}(i-j)^2$$
$$Energy = \sum_{i,j=0}^{n-1} (p_{i,j})^2$$
$$Entropy = -\sum_{i,j=0}^{n-1} p_{i,j}(log p_{i,j})$$
$$Correlation = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} ij p_{i,j} - \mu_x\mu_y}{\sigma_x\sigma_y}$$
$$Homogeneity = \sum_{i,j=0}^{n-1} p_{i,j}/(1+(i-j)^2)$$

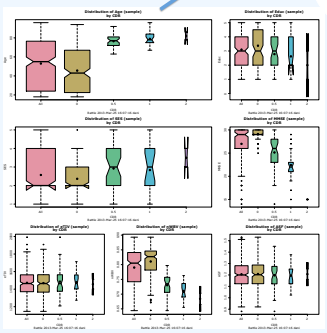
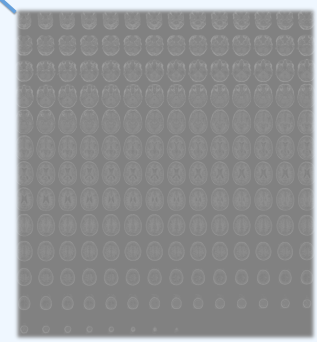


Figure 1. Box-plot describing the OASIS dataset in terms of CDR, given (A) age, (B) SES, (C) mini-mental state examination or MMSE, (D) estimated total intracranial volume or eTIV, (E) normalized whole-brain volume or nWBV, (F) atlas scaling factor or ASF



GLCM is constructed from the image by estimating the pairwise statistics of pixel intensity, computing the number of transitions (#) from pixel *i* to *j*. Consider the function ρ to be the resultant transition from $i=I_g(x,y)$ to $j=I_g(x,y)$ for a distance *d* and angle Θ, so ρ can be expressed as:

$$p(i,j|d,\theta) = \#\{(i,j) \in I_g \mid j = \rho(i|d,\theta)\}$$

Considering 4 directions:

$$\rho(i|d,\theta=0^o) \rightarrow \bar{x} = x+d; \quad \bar{y} = y;$$
$$\rho(i|d,\theta=45^o) \rightarrow \bar{x} = x+d; \quad \bar{y} = y+d;$$
$$\rho(i|d,\theta=90^o) \rightarrow \bar{x} = x; \quad \bar{y} = y+d;$$
$$\rho(i|d,\theta=135^o) \rightarrow \bar{x} = x-d; \quad \bar{y} = y+d;$$

Then, the GLCM for each angle with its transposed matrix result in the isotropic matrix:

$$p_{iso} = \sum_{\theta=0,45,90,135} \frac{(p_\theta + p_\theta^T)}{8}$$

References:
[1] D. Marcus, Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults, J Cogn Neuroscience, 2007.
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[3] D. M. Ushizima-Sabino et al, A texture approach to leukocyte recognition, Real-Time Imaging 10(4): 205-216.
[4] Haralick RM. Statistical and structural approaches to texture. Proc. IEEE, vol. 1979; 67(5): 786-804.
[5] ALZHEIMER'S DISEASE NEUROIMAGING INITIATIVE datasets: http://adni.loni.ucla.edu/data-samples/mri/

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We thank Daniel Marcus for his valuable comments about the OASIS database, including remarks about the intensity normalization in the processing stream, so that we were able to consider textural analysis without interference of inhomogeneities. This work was partially funded by the U.S. Department of Energy under Contract No. DE-AC02- 05CH11231.