Automated evaluation of structural characteristics and extension of cerebral gliomas using DTI-MR 3D Texture Analysis

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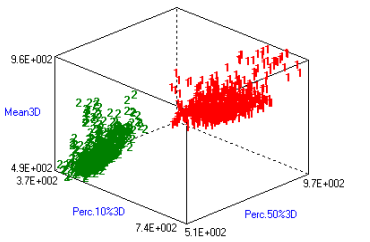
Background

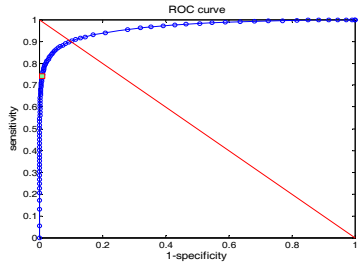
The diffuse and infiltrative growth of cerebral gliomas is a major determinant of poor prognosis. Tumor cells invade surrounding tissues preferentially along white matter tracts [1], spreading beyond the abnormal area seen on conventional MR images [2]. The detection and characterization of this microscopic infiltration in a non-invasive manner is of outstanding importance for surgical and radiation therapy planning or to assess response to chemotherapy. Diffusion tensor imaging can reveal larger peritumoral abnormalities in gliomas that are not apparent on conventional MR imaging, by detecting the presence of microscopic tumor cells infiltration in white matter around the edge of the gross tumor [3], as confirmed by image guided biopsies [4].
The aims of this study are: 1) to characterize pathological and healthy tissue in DTI datasets by 3D statistical Texture Analysis, developing an automated segmentation technique of cerebral tumors; 2) to correlate segmentation results with histopathological findings from specimens obtained from image-guided tumor biopsies.

Material and Methods

Twelve patients with glioma (6 low-grade, 6 high-grade) were selected. 3T MR-DTI consisted of a single-shot EPI sequence (TR/TE 8986/80 ms) with parallel imaging (SENSE factor, R = 2.5). 32 diffusion gradient directions (b=1000 s/mm^2) and one image set without diffusion-weighting were obtained. The sequence was repeated two consecutive times and data were averaged off-line to increase signal-to-noise ratio; DTI datasets were aligned off-line to the echo-planar volume without diffusion weighting on a PC workstation using the AIR (Automatic Image Registration) software to correct artifacts due to rigid body movement during scan acquisition. T2-weighted FSE and T1-weighted FFE conventional imaging was performed for anatomic guidance and morphological characterization of the lesions.
Diffusion maps were obtained using an in-house software implemented in MATLAB to produce fractional anisotropy (FA) and mean diffusivity (MD) maps, and *p* and *q* maps (the isotropic and anisotropic components of the diffusion tensor). Manual segmentation of pathological areas was performed on each map; 3D texture analysis was applied to the segmented ROIs, and features from the intensity histogram, the gradient histogram, the cooccurrence matrix (COM) and the run length matrix (RLM) were calculated with a sliding window approach. In order to identify discriminating features, statistics were also calculated in the corresponding contralateral ROIs (healthy tissue). After determining the most discriminating features according to their Fisher-filter score, the feature-space dimensionality was reduced by PCA (Principal Component Analysis) application, and a supervised classifier based on a back-propagation, feed-forward artificial neural network (ANN) with a 3-neuron hidden layer was trained. Its quality was tested by ROC (Receiver Operating Characteristic) curve calculation. Glioma segmentations were performed and compared with manual ones; patients underwent surgery with the aid of a neuronavigation system, onto which segmentation results were transferred as described in [1], in order to allow direct correlation between the tumor margins depicted by DTI and histopathological intraoperative findings.



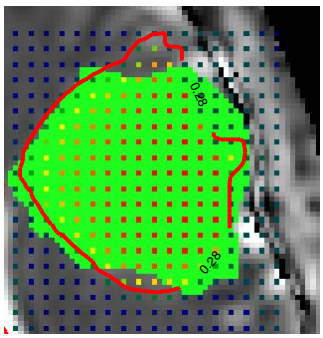
▲*Fig.1: Scatter plot of three of the best features, for the p map. Red 1's are pathological sub-ROIs, while green 2's represent the corresponding contralateral healthy regions.*



▲*Fig.2: ROC curve for the p map classifier; the square dot on the graph highlights the configuration with ANN output threshold equal to 0.5*

Results

Six patients were employed for training, six for testing. The most discriminating *features* were selected for each map according to the Fisher filter (Fig.1). Classifier sensitivity, specificity and ROC curves were calculated, as displayed in Fig.2: preliminary results were obtained for the *p* map (AUC = 0.96, sensitivity and specificity equal to 90% at ANN threshold equal to 0.28, with a classification error of 10.0%) and FA map (AUC = 0.98, sensitivity and specificity equal to 92.6% at ANN threshold equal to 0.25, with a classification error of 7.3%). Test images were automatically segmented by tissue classification; manual and automatic segmentations were compared as shown in Fig.3. In the first four patients, all image-guided biopsies obtained along tumor margins depicted by DTI segmentations showed neoplastic infiltration. Tumor infiltration area corresponded to the area depicted on *p* maps (increase in the isotropic component); gross tumor core corresponded to the area depicted on *q* maps (reduction of anisotropic component) smaller than *p* area. Tumor cell density decreased from gross tumor core to periphery in the difference area between *p* and *q*.



▲*Fig.3: The CAD probability map is displayed by a parallelepiped grid of color dots, where cold colors correspond to lower, and warm colors to higher malignancy likelihood,. Each dot is the center of the sliding window. The red line is the result of CAD segmentation. The green region is the physician ROI.*

Discussion and Conclusions

The preliminary results of this study show good concordance between manual and automatic segmentations, and are confirmed by histopathological intraoperative findings. Our approach looks promising for preoperative assessment of structural heterogeneity and extension of cerebral gliomas. It could allow objective tumor identification and quantitative measurement, especially in view of a patient follow-up during chemotherapy; it could be proposed as a part of an integrated approach, beside other MR advanced techniques like MR spectroscopy and perfusion, to evaluate response to therapy. In the next future other texture features and different classifiers will be tested, looking for optimal performance.

[1] Bello L et al. Neuroimage 2008; 39(1):369-82 [2] Price SJ et al. Eur Radiol 2004;14(10):1909-17. [3] Price SJ et al. AJNR 2006;27(9):1969-74. [4] Price SJ et al. Eur Radiol 2007;17(7):1675-84.