Does brain tumor classification improve on fusion of MRI and short echo time MRSI?

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Introduction

Magnetic Resonance Imaging (MRI) and MR Spectroscopic Imaging (MRSI) play an important role in the noninvasive diagnosis of brain tumors. However, fusion of the two is not often considered during classification. This is regrettable since both can be performed on the same clinical system during the same session, and at present computational power is sufficient to handle the (huge) multivariate datasets. In order to optimally classify brain tumors we fused MRI with feature reduced MRSI, and compared the results of a multi-class classifier and several binary classifiers with classification without MRI.

Methods

Expert selected voxels from a set of 24 patients and four volunteers were used to configure a dataset of 669 samples. Each voxel was considered to belong to a specific class, based on its location in the brain or tumor and the histopathological determined type of the tumor. The dataset was split into six classes of WHO grade II, III and IV glial tumors, meningioma, healthy tissue and cerebro-spinal fluid. During data acquisition, conventional T_1-, T_2-, proton density-, and gadolinium-DTPA enhanced T_1-weighted images were collected (T_1, T_2, PD and GD images). In case of a volunteer, the GD image was replaced by the T_1 image, since for these subjects no GD image was available. Next, 2D-STEAM ^{1}H-MRSI was performed with the following parameters: 16x16x1024 matrix size, FOV: 200 mm, TR = 2000 or 2500 ms, TE = 20 ms. The MRSI was zero-filled to obtain a 32x32 spatial grid, and the spatial resolution of the images was decreased to meet this resolution. From each spectrum (obtained after 3D FFT of the MRSI k-space data) intensities of 8 spectral ranges were determined by integrating the intensities of a window of 0.13 ppm around; 3.56 (myo-inositol), 3.44 (glucose), 3.20 (choline), 3.02 (creatine), 2.20 (glutamate/glutamine), 2.02 (NAA), 1.33 (lactate), and 0.90 ppm (fatty acids). After processing, eight spectral and four image variables were available for each voxel. For the binary classification additional MRSI intensities from 3.75 (alanine) and 3.95 ppm (creatine) were taken into account.

Overlap of classes in feature space was visualized by plotting the cumulative sum of objects for each class within a certain Mahalanobis distance to the centroid of one specific class[1]. Plots were made for each class using MRSI data alone, and MRI fused with MRSI data. Next, the dataset was split into a training (2/3) and test (1/3) set. Classification using the Mahalanobis distance with respect to each class was performed as criterium, to compare multi-class classification of MRSI versus MRSI+MRI. Next, binary classifiers were developed for the classes that were still difficult to separate. These classifiers were based on Least Squares Support Vector Machines (LS-SVM) with a nonlinear Radial Basis Function[2].

Results

The distribution plots show that all classes have less overlap when additional MRI information is used. In figure 1 the plots are shown for the grade II and III class using MRSI (top left and right) and MRSI+MRI (lower left and right). The best classification result is obtained with a feature space that generates the largest cross-hatched area in a subplot. The multi-class classifier has a higher sensitivity for all classes when MRI is fused with MRSI. The normal tissues are classified with 100% sensitivity (compared to 87%), as well as the meningiomas (compared to 77%). The mean sensitivity of the glial tumors increases from 80% to 87%. The separation between grade II and III glial tumors remains difficult.

To separate the problematic gliomas, binary classifiers are build to separate low- from high-grade gliomas (gr. II vs. III+IV), grade II from grade III gliomas and grade II from grade IV gliomas. Fusion of information from MRI and MRSI increases performance slightly, as shown in the classification rates in table 1.

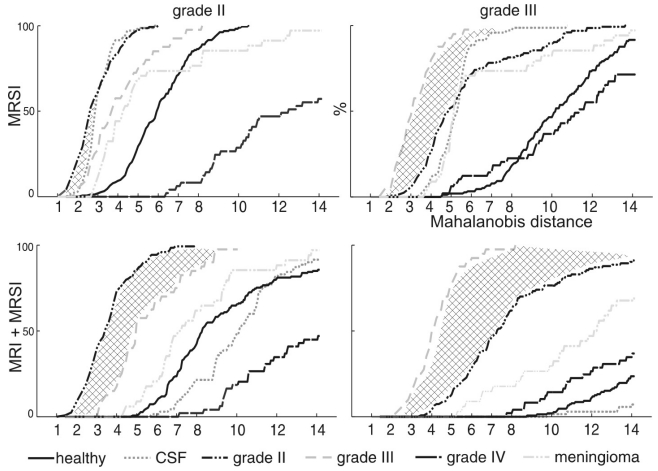

Fig. 1: Distribution plots show less overlap when MRI and MRSI are fused.

Table 1: Binary classification using nonlinear LS-SVM. Average test performance (mean correct classification rate (%) and its pooled standard deviation).

classes	MRI	MRSI	MRI + MRSI
II vs. III + IV	80.1 ± 3.8	95.0 ± 2.1	96.8 ± 1.8
II vs. III	85.9 ± 3.0	94.4 ± 2.5	95.9 ± 2.4
II vs. IV	87.9 ± 3.1	98.6 ± 1.0	98.1 ± 1.5

Conclusions

We show that fusion of MRI and MRSI data improves the classification of brain tumors and normal tissues using a multi-class classifier as well as several binary classifiers. Fusion of medical data along with specialized classifiers seems to be promising for tumor diagnosis. This suggests that fusion of MR data with other imaging techniques -like CT or PET- or clinical information may contribute to a better brain tumor classification. However, this will need the development of easily accessible and transparent databases that contain medical information.

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[1] Simonetti AW, et al., Analytical Chemistry 75(20), 5352-5361, 2003
[2] Devos A, et al., submitted, 2004, http://www.esat.kuleuven.ac.be/scd