Multiple Sclerosis Clinical Classification Based on DTI Fiber Analysis

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Target audience: Researchers in diffusion MRI, neuroimaging processing, neurobiologists, neurologists and MR technologists.

Purpose: Diffusion tensor imaging (DTI) provides greater sensitivity than conventional MRI to detect diffuse alterations in normal appearing white matter (NAWM) of Multiple Sclerosis (MS) patients [1]. This high sensitivity level could be exploited to perform automatic classification of MS patients' clinical forms with machine learning algorithms. In this work, we present a fully automated Support Vector Machine (SVM) method for subject classification in three groups (healthy control (HC) subjects, relapsing-remitting (RR) and primary progressive (PP) MS patients) based on the diffusion information obtained from several WM fiber bundles.

Materials and methods: Forty-three MS patients (25 RR and 18 PP) and 26 HC subjects were examined on a 1.5 T MR Siemens Sonata system. DTI data were acquired using a spin-echo EPI sequence (TR=6900ms, TE=86ms) with 96 x 96 phase-encodings over a field of view of 240 x 240 mm and 51 axial slices of 2.5 mm thickness. Post-processing of DTI data was performed using FSL [2]. Fractional anisotropy (FA), radial diffusivity (RD) and mean diffusivity (MD) maps were first generated. All diffusion maps were then non-rigidly registered to the Illinois Institute of Technology atlas (IIT3) [3] (Fig. 1). Ten fiber bundles were then extracted from the JHU-Atlas [4]: major and minor forceps of the Corpus Callosum (CC), left (L) and right (R), Cortico-Spinal Tract (CST), Inferior Fronto-Occipital Fasciculus (IFOF), Anterior Thalamic Radiation (ATR), and Uncinate Fasciculus (UC). Diffusion values obtained from the fiber bundles voxels were then used as features for the classification task. For each fiber bundle, the 1000 most relevant features were selected with the RELIEF attribute selection algorithm [5]. The chosen data were finally classified using SVM [6] with a RBF Kernel (C=1.0 and γ=0.01) and by performing a 10 K-Fold cross validation (Fig. 2).

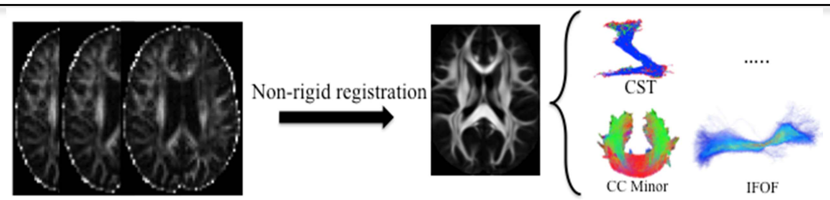

Figure 1: Pipeline for data registration on MNI standard space and fiber bundle extraction

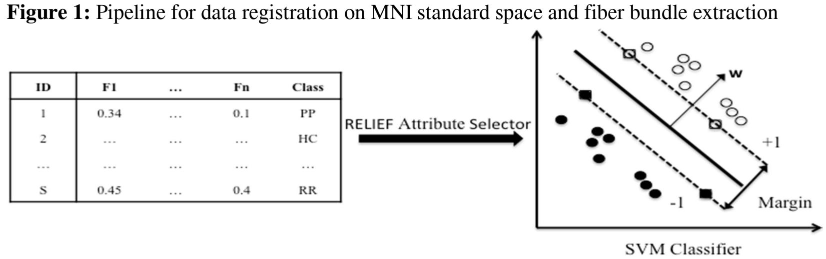

Figure 2: Application of RELIEF attribute selection on raw voxel data and classification using SVM classifier

Results: The classification performances were analyzed by measuring the accuracy, precision and ROC Area for the three diffusion metrics in all the fiber bundles (Table 1). The highest classification was achieved with RD and FA. Indeed, for RD values, accuracy ranged between 71.0% and 85.5% (mean=79.0%), precision ranged between 70.5% and 85.6% (mean=79.0%) and ROC Area ranged between 0.78 and 0.89 (mean=0.84). Similarly for FA, accuracy ranged between 73.9% and 85.5% (mean=80.0%), precision ranged between 72.8% and 86.7% (mean=80.0%) and ROC Area ranged between 0.80 and 0.89 (mean=0.84). The best classification performance was reached for RD in the left IFOF and FA in the right IFOF. High levels of classification performances were also reported in CST, forceps major and right UN.

Discussion: The use of SVM combined to DTI measures demonstrated higher degrees of classification performances in terms of accuracy, precision and ROC Area. The resulting performance values suggest that each WM fiber bundle contributes differently to the classification analysis. Indeed, certain fiber bundles, namely CST, IFOF and forceps major presented a more accurate classification compared to the others. Moreover, we showed that the classification result depends on the diffusion metrics used to study a specific fiber bundle. This result could be useful to identify a specific diffusion metric that better characterizes the WM fiber bundle properties.

		CC Major	CC Minor	CST L	CST R	IFOF L	IFOF R	ATR L	ATR R	UN L	UN R
Accuracy (%)	RD	76.8	78.3	78.3	84.1	85.5	73.9	82.6	82.6	71.0	76.8
	MD	78.3	72.5	81.2	81.2	73.9	81.2	76.8	76.8	73.9	73.9
	FA	84.1	81.2	75.4	82.6	75.4	85.5	73.9	73.9	79.7	84.1
Precision (%)	RD	77.0	80.0	78.7	84.2	85.6	73.7	82.8	83.7	70.5	76.4
	MD	78.4	71.7	80.8	81.0	72.8	81.3	76.8	76.4	74.0	73.7
	FA	84.0	81.7	76.4	82.8	75.7	85.9	72.8	74.0	81.0	86.7
ROC Area	RD	0.83	0.82	0.83	0.88	0.89	0.80	0.87	0.87	0.78	0.82
	MD	0.79	0.84	0.86	0.86	0.80	0.86	0.83	0.82	0.80	0.80
	FA	0.86	0.88	0.81	0.87	0.81	0.89	0.80	0.80	0.84	0.87

Table 1. Average measures of the classification performances: accuracy (%), precision (%) and ROC Area, based on diffusion metrics in right (R) and left (L) extracted fiber bundles

Conclusion: We presented a fully automated method for the classification of subjects in three different groups (HC, RR, PP) based on the analysis of diffusion metrics extracted from 10 major WM fiber bundles. The classification results obtained with the SVM classifier, confirmed the ability of DTI to characterize MS pathological processes. Moreover, different fiber bundles contributed differently to the identification of the pathology.

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