Detection of spinal cord abnormality on Diffusion Tensor Imaging (DTI) in patients with unilateral deficit using pattern classification

A. Cardenas-Blanco[1], S. Chakraborty[2], F. Alkherayf[3], E. Tsai[3], M. Schweitzer[2], and T. Nguyen[2]
[1]Diagnostic Imaging Department, The Ottawa Hospital, Ottawa, Ontario, Canada, [2]Radiology, The Ottawa Hospital, Ottawa, Ontario, Canada, [3]Neurosurgery, The Ottawa Hospital, Ottawa, Ontario

Introduction: Conventional magnetic resonance imaging in the spinal Cord (SC) is often insufficient to diagnose, asses the stage and progression of disease [1]. Abnormalities seen on conventional MRI are often unreleated to clinical findings. During the last years, Diffusion Tensor Imaging (DTI) has become the preferred tool to analyze white matter properties, fibre organization and mobility of the water molecules, reflected by Fractional Anisotropy (FA) and Mean Diffusivity (MD) respectively. To reduce the discrepancies between MR findings and clinical presentations we introduce a new model to analyze spinal cord images based on pattern classification. Looking at the interrelationship of quantitative MR parameters in healthy spinal cord, a pattern classification algorithm was trained and tested in patients with unilateral deficits.

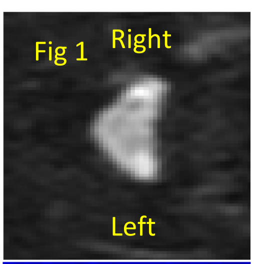
Theory: By combining FA, MD and T2 weighted signal intensity values; obtained from the DTI obtained from healthy asymptomatic controls,, we studiedd their interrelationship to build a model of healthy SC using pattern classification algorithm. The obtained model was used to locate and identify abnormalities in the cord (by exclusion). After processing the MR images, each pixel in the spinal cord was characterised by three parameters, FA, MD and T2, which defined the so called feature vector, **x**. In our case, since the form of the underlying density functions was not known, the Parzen-window approach was used for estimating the density functions, $p_n(x)$ (Eq 1) and applied it in a parallel fashion to implement a probabilistic neural network (PNN)[2]. To facilitate the inter-subject comparison, the T2 weighted signal intensity was normalized by the maximum T2 signal intensity value of CSF at each level in all subjects.

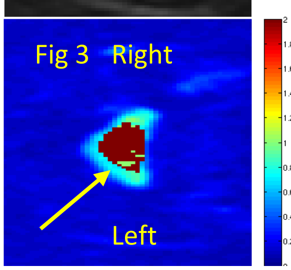
Methods: Aproval from the local Research Ethics Boards was obtained. MR images were obtained from a total of 8 healthy controls and 5 patients with unilateral deficits due to cervical spondylosis. The DTI acquisition was performed using an axial spin-echo echoplanar parallel grappa diffusion weighted imaging sequence with acceleration factor 2; 12 non collinear gradient directions were applied with two b-values (b=0 and b=600 s/mm2) field of view 180 x 180 mm; 17 slices and a thickness of 5 mm; extending from C2 to C6 in controls and at different cervical levels depending on the pathology in patients. FA and MD maps of the SC were obtained after processing the images with the FSL package. Two experienced neuroradiologists were asked to segment healthy spinal cord tissue using the DTI b0 images obtained from the healthy control subjects; this information was used to train the algorithm on how the feature values are interrelated in healthy spinal cord. Subsequently, the radiologists segmented spinal cord of the patients. The feature vectors obtained from the patient segmentation, at the level of the lesion, were compared using a probability neural network algorithm to see whether those feature vectors were similar or not to the ones obtained from the healthy controls at the same cervical level, used for training.

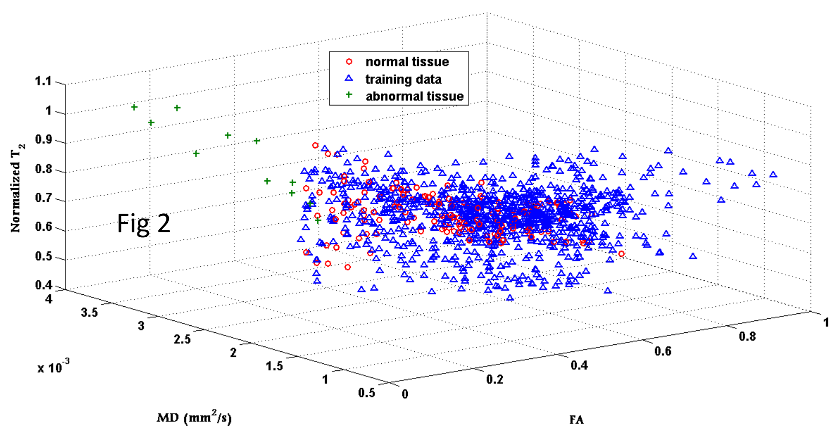
$$p_n(x)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{V_n}\varphi\left(\frac{x-x_i}{h_n}\right) \quad [1]$$

Results: After selecting the spinal cord ROI on the b0 image (figure 1), the obtained feature vectors are compared to the training data sets obtained from the healthy controls, the results obtained after running the classification algorithm can be seen in figure 2. The blue triangles, training data set at the C6 level obtained from all controls, the red circles, patient data classified as "normal tissue", the green crosses, patient data classified as "abnormal tissue". The yellow arrow in figure 3, points to the location of the abnormal tissue in the spinal cord image, on red, normal tissue, on green abnormal tissue; an area which comprehends the spinal thalamic tracts. This result matches with the patients symptoms, who suffered from sensory changes in the right arm (C6 dermatome). In general the abnormalities detected in the patient by observer 1 and observer 2 using conventional T2 weighted images matched the clinical symptoms in 1 and 3 of the cases respectively. The results obtained by the classification algorithm and observers were compared to the truth obtained from the clinical symptoms using a Wilcoxon rank sum test. For observers 1 and 2, the null hypothesis, medians are equal, can be rejected, p= 0.04 and p=0.44, the results obtained by the classification algorithm indicates that the null hypothesis cannot be discarded, p=1, hence demonstrating that the algorithm has obtained the most accurate results.

Conclusion: Given the appropriate training, pattern classification algorithms are a promising technique in the study and analysis of DTI among other MR image modalities. Their main advantage is their ability to combine multivariate information to find differences between normal and abnormal tissue in a semi-automated fashion which allowed the identification of localized abnormal tissue (spinal thalamic tracts, corticospinal tracts, etc) that matched the clinical symptoms in all 5 cases.







References:
[1] Coronado R et al, Correlation of magnetic resonance imaging finding and reported symptoms in patients with chronic cervical dysfunction. 2009;17(3)148-153 [2] R. Douda et al, Pattern Classification, Wiley Interscience 2001.