

INTRODUCTION

In this study we focus on the problem of segmenting the inner structures of the spinal cord on magnetic resonance images (MRI). The spinal cord consists of surrounding white matter (WM) and inner gray matter (GM) with a cross-sectional butterfly shape (Fig.1). Low resolution and low contrast between WM/GM in images (Fig.2) make this task difficult. In the MR images, GM is displayed brighter than WM.

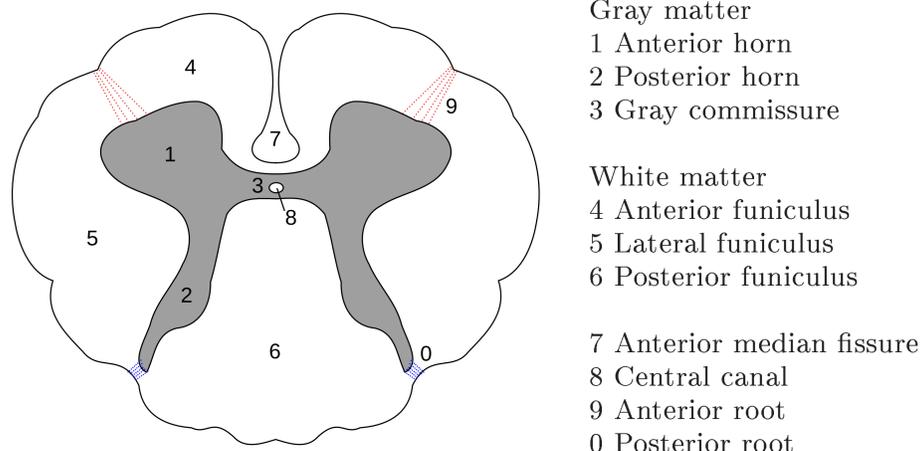


Fig. 1: Schematic cross-section of the spinal cord.

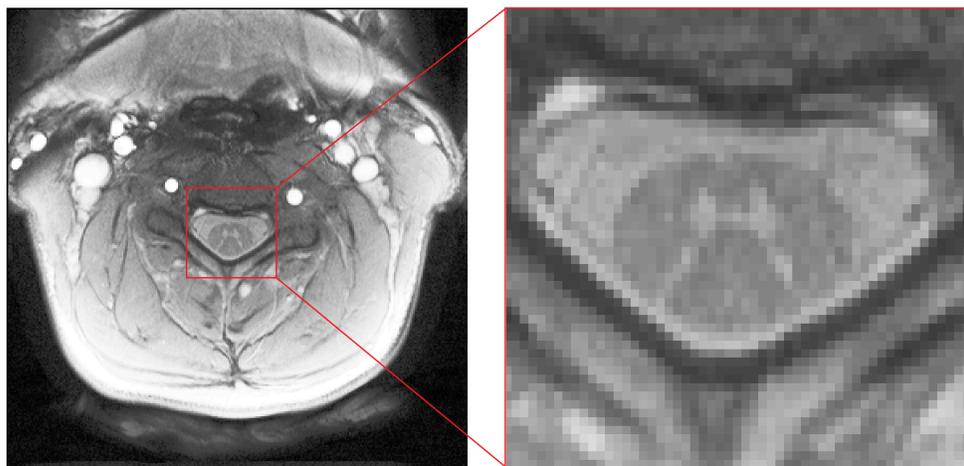


Fig. 2: Axial cross-section, MOLLI sequence [1], 0.4 mm × 0.4 mm.

The aim of this study is automated segmentation for the spinal cord to better understand the effect of multiple sclerosis on WM/GM. The segmentation model should have the following properties: subpixel accuracy, precision, robustness and automated localization.

RESULTS

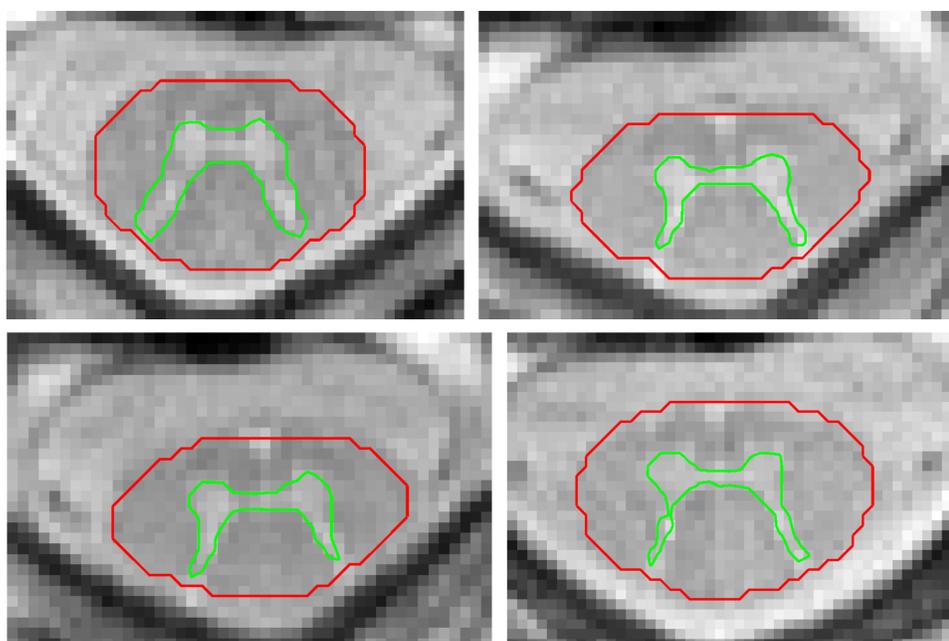


Fig. 3: Segmentation results of the current approach [3].

MATH BACKGROUND

In an abstract view we can describe a segmentation process as an optimization problem, where we define a function space V for the admissible labeling functions and an energy functional E with the optimal segmentation as minimal state:

$$\min \{E(u) \mid u \in V\}.$$

Numerically the functional optimization problems can be solved with iterative descent algorithms, whose steps can be seen as solutions of partial differential equations (PDE). The gradient descent equation

$$\frac{\partial u}{\partial t} = -\frac{\delta E}{\delta u}$$

builds the connection between functional formulation and PDE based segmentation. E often is defined as an integral operator with Lagrangian F dependent on u and ∇u , and thus the variational derivative can be calculated through

$$\frac{\delta E}{\delta u} = \frac{\partial F}{\partial u} - \operatorname{div} \frac{\partial F}{\partial \nabla u}.$$

WM/GM SEGMENTATION MODEL

Our idea is to minimize

$$\int_{\Omega} \lambda (I - I_{\text{model}})^2 + \mu (I_{\text{model}} - I_{\text{prior}})^2 + C \|\nabla u\|_A dx, \quad (1)$$

where we segment a relaxed piecewise constant Mumford-Shah approximation $I_{\text{model}} = c_0 u + c_1 (1 - u)$ of the MR image I and force the segmented result to be close to a prior I_{prior} by minimizing the mean squared distances. The relaxed labeling function u discriminates between WM/GM. By factoring out with remainder, we see [2] that energy (1) can be minimized by a continuous cut algorithm. To a resulting continuous cut energy

$$\int_{\Omega} C_t u + C_s (1 - u) + C \|\nabla u\|_A dx + \nu BC(u)$$

we add an additional Bhattacharyya Coefficient BC . The terminal capacities C_t , C_s and the non-terminal capacity C are designed to cope with (1) and are varied over the numerical iteration time [3]. The Riemannian metric matrix field A anisotropically regularizes the total variation of u .

The non-convexity of BC and the local behavior of $\frac{\delta BC}{\delta u}$ is guided by the convex property of the continuous cut and helps the cut to adjust to local image intensity differences.

REFERENCES

- [1] Weigel *et al.* A Simple and Fast Approach for Spinal Cord Imaging with High Resolution and Good Contrast, 2016
- [2] Overgaard *et al.* Pose Invariant Shape Prior Segmentation Using Continuous Cuts, 2009
- [3] Horváth *et al.* Variational Segmentation of WM/GM in the Spinal Cord using a Shape Prior, 2016