Automatic Detection of the Spinal Cord Centerline using Machine Learning and Global Nonlinear Optimization

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Plan

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- Symptoms :
  - loss of sensation
  - loss of coordination
  - pain
  - paralysis

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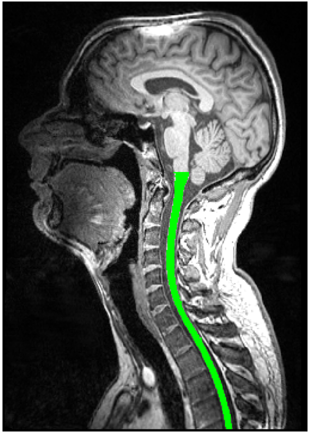

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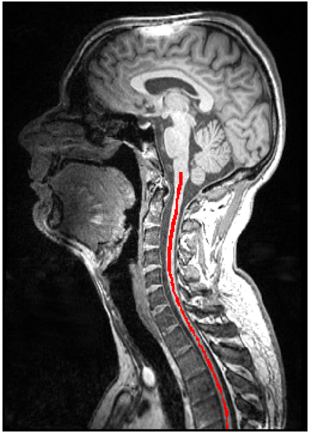

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- Image registration : atlas based segmentation, group studies, morphometry, motion correction
- Image segmentation : atrophy measurement, physiological parameter measurement
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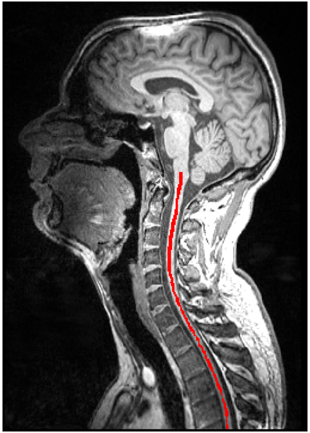
  - Can be used as an initial step for all processing
  - Nothing satisfying in the literature if we want to be
    - robust to image resolution
    - robust to pathologies
    - robust to contrast, MR scanner



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Using Machine Learning for Spinal Cord Localization

$$SCC(p) = \begin{cases} > 0 & \text{if SC} \\ < 0 & \text{otherwise} \end{cases}$$

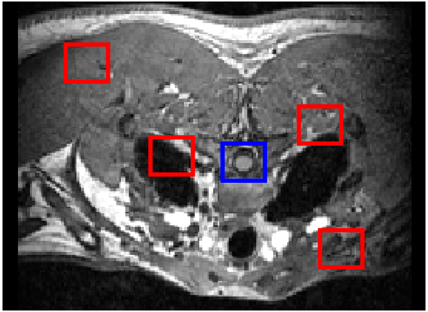
$\uparrow$

Spinal Cord Classifier

$\uparrow$

p=patch

Using Machine Learning for Spinal Cord Localization



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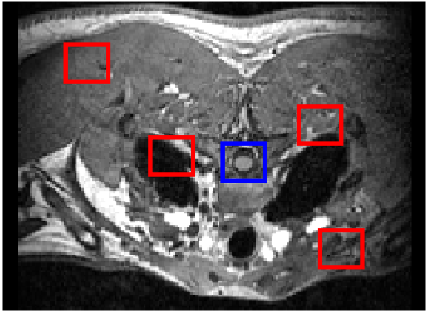

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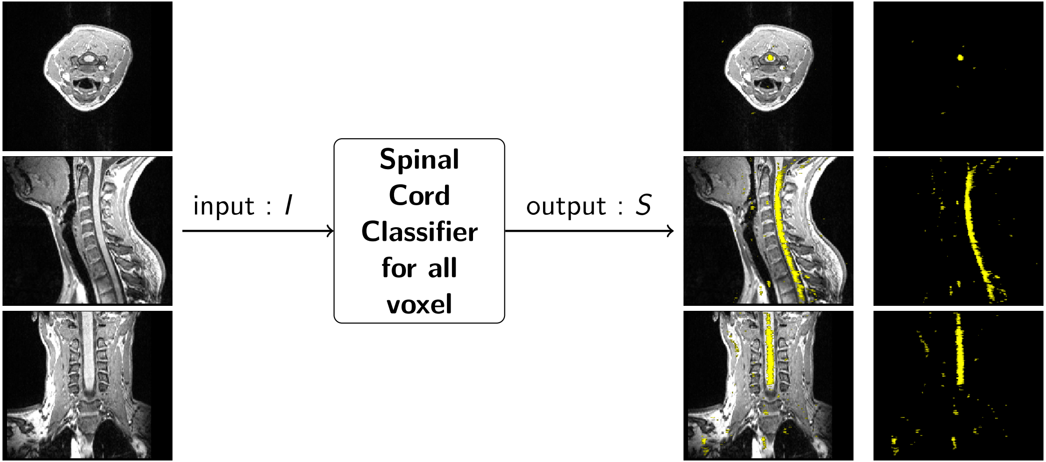
HOG feature with linear SVM classifier (Dalal & Triggs 2005)

Computing a Localization Map



Centerline Extraction

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- Proposition : solve

$$\min_{c_0,\dots,c_{n-1}} -\sum_{z=0}^{n-1} S_z(c_z) + \lambda \sum_{z=0}^{n-2} \|c_{z+1} - c_z\|^2 ,$$

  - local optimization (gradient descent) : fast, not robust
  - global optimization : robust, very slow (brute force : exponential)

Fast Global solution of the optimization problem

Solve

$$\min_{c_0,\ldots,c_{n-1}} C_{n-1}(c_0,\ldots,c_{n-1}) = -\sum_{z=0}^{n-1} S_z(c_z) + \lambda \sum_{z=0}^{n-2} \|c_{z+1} - c_z\|^2 ,$$

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Define :

$$M_k(x_k) = \min_{x_0,\ldots,x_{k-1}} C_k(x_0,\ldots,x_{k-1}).$$

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Solution on the last slice :

$$\min_{x_{n-1}} M_{n-1}(x_{n-1}) = \min_{x_0,\ldots,x_{n-1}} C_{n-1}(x_0,\ldots,x_{n-1})$$

Fast Computation of the M_k sequence

Distance/NN transform for greylevel image (Meijster 2002, Felzenszwalb 2012) :

$$D(f)(x) = \min_y f(y) + \|x - y\|^2 \qquad N(f)(x) = \operatorname{argmin}_y f(y) + \|x - y\|^2$$

f

$D(f)$

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$$\begin{aligned} M_k(x_k) &= -S_k(x_k) + \lambda \min_{x_{k-1}} \left\{ \frac{M_{k-1}(x_{k-1})}{\lambda} + \|x_k - x_{k-1}\|^2 \right\} \\ &= -S_k(x_k) + \lambda D\left(\frac{M_{k-1}}{\lambda}\right)(x_k) \end{aligned}$$

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\end{aligned}
$$

If c_k is known, then c_{k-1} is given by

$$
\begin{aligned}
c_{k-1} &= \operatorname*{argmin}_{x_{k-1}} \frac{M_{k-1}(x_{k-1})}{\lambda} + \|c_k - x_{k-1}\|^2 \\
&= N\left(\frac{M_{k-1}}{\lambda}\right)(c_k)
\end{aligned}
$$

Fast Centerline Extraction Algorithm : linear complexity

Algorithm 1 Center Line Extraction Procedure

procedure *ExtractCenterLine*(S, λ)
  $M_0 = -S_0$
  for z=1 :n-1 **do**
    $M_z = -S_z + \lambda D\left(\frac{M_{z-1}}{\lambda}\right)$
    $N_z = N\left(\frac{M_{z-1}}{\lambda}\right)$
  $c_{n-1} = \mathrm{argmin}_x M_{n-1}(x)$
  for z=n-2 :0 **do**
    $c_z = N_{z+1}(c_{z+1})$

Fast Centerline Extraction Algorithm : linear complexity

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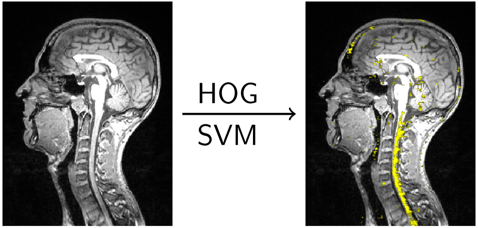
Fast Centerline Extraction Algorithm : linear complexity



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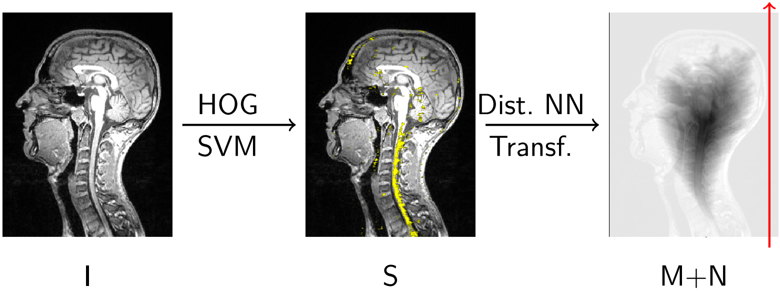

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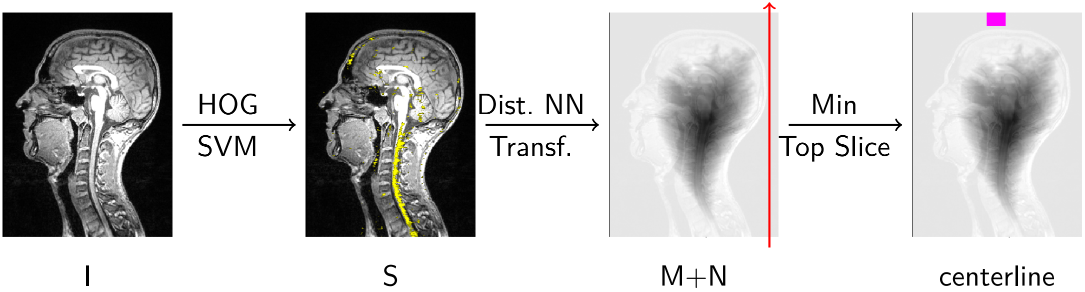

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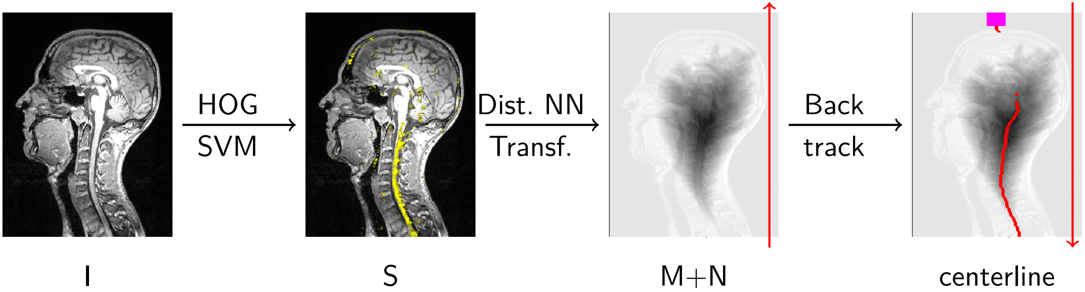


Plan

Introduction

Method

Results

Conclusion

Dataset

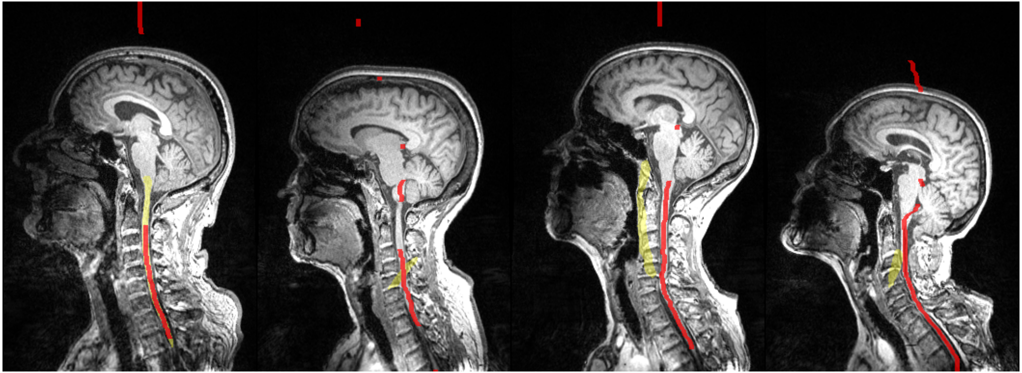
- 3D T_1 MRI acquired at the CRMBM (Marseille)
- 8 images from healthy control subject
- 8 images from subject with pathology (MS, compression)
- voxel size : $1mm \times 1mm \times 1mm$
- matrix : $176 \times 264 \times 384$

Computation time

Localization map		Global Optimization
1 Core	8 Cores	
17	2	0.4

CPU time in second

Visual Examples : Comparison with sct-propseg (De Leener 2014)



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Evaluation Criterion : detected centerline inside/outside the true spinal cord
Results reported for slices with spinal cord only.

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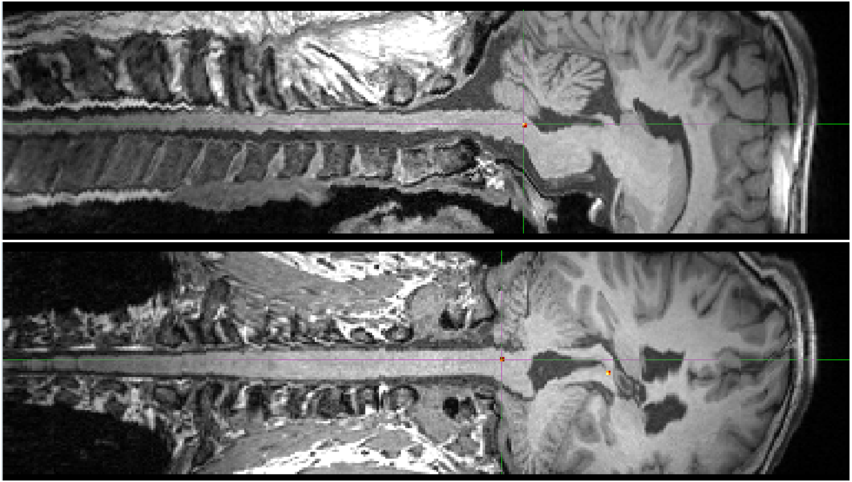
	sct-propseg	Classifier Only $\lambda = 0$	Regul + Glob. Opti $\lambda = 1$
Controls	25$\pm$ 32	30 $\pm$17	0.8 $\pm$1
Patients	55$\pm$ 45	25 $\pm$07	3.0 $\pm$4

Error percentage : mean/std-dev percent of slices with the centerline outside the true spinal cord

Brain Vs Spine Separation : Preliminary Results



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- Ongoing Work : Large Scale evaluation (with NeuroPoly, Polytechnic Montréal)
  - about 500 subjects
  - Multiple MRI contrast (T_1, T_2, T_2^*, DWI)
  - Multiple imaging center
  - large variety of image resolution
  - large variety of pathology (MS, ALS, trauma,...)

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- Soon freely available for academic (CREATIS website + Spinal Cord Toolbox)

Acknowledgments

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Thanks for your attention ! !