

Segmentation of Nerve Bundles and Ganglia in Spine MRI using Particle Filters Adrian Dalca¹, Giovanna Danagoulian², Ron Kikinis^{2;3}, Ehud Schmidt², and Polina Golland¹

Background

Motivation

- New high-res MRI visualization of **nerve bundles** from inside to outside of vertebral canal
- Segmentation of bundles useful for spinal pathologies diagnosis, treatment planning and \bullet image-guided interventions
- Manual segmentation is **time-consuming & challenging** impractical to construct nerve maps

GOAL: Provide an automatic segmentation method for nerve bundles and ganglia in spinal MRI.





MRI slices showing nerve bundle, pathology and ganglia

Related Work

Most relevant work is vessel segmentation. Assumptions and requirements differ from nerve data

- Region-growing approaches (problems: leakage, sensitive to contrast) \bullet
- Active contour methods (problems: good initialization, sensitive to leakage) \bullet
- Centerline extraction (problems: interactive re-seed, endpoints, sensitive to tissues) \bullet

Our Approach

• Tracking approach based on **particle filters** with minimal input requirement



Nerve Segments - Particles







Entire volume



Volume: 512x512x100 voxels Voxel: 0.5x0.5x1.0mm

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Illustration of nerve bundles (Google Body)

Observation \mathbf{z}_t



Particle: 15-30 voxels long x 2-15 voxels wide Observation: particle length, 2x particle width

Initialization

Two manual clicks – generate a

For each successiv Goal: obtain a particle set given

Sample particles from

Propagate particles 2)

- Require **continuity** and **sn**
- Encourage consistent nerv

Weigh particles base 3)

• weight =
$$p(\mathbf{z}_t | \mathbf{h}_t) \propto e_t$$

$$d_{\mu}^{2} = \left[\mu_{t} - \frac{1}{|V|} \sum_{v \in V} I \right]^{2}$$
$$d_{\nabla}^{2} = \frac{1}{|V|} \sum_{v \in V} ||\hat{g}_{v}^{h} \times \hat{g}_{v}^{I}||$$

These steps form samples fr $\boldsymbol{h}_t \sim p(\boldsymbol{h}_t | \boldsymbol{z}_{1:t})$

Post-Processing cl

- Tracks that were not re-sampled
- Entire tracks are **re-weighed** wit
- **Top tracks** are selected as final output

segmentations for centerlines & surfaces

- Ten nerve bundles from five subjects
- Strong core and path estimation



- Demonstrated **successful tracking** on spinal MRI dataset

Algorithm

set of weighed particles approximating $p(h_1 z_1)$	
ve step t: observations $z_{1:t}$ approximating posterior $p(h_t z_{1:t})$	
$p(h_{t-1} z_{t-1})$	
via dynamics model $p(\boldsymbol{h}_t \boldsymbol{h}_{t-1})$	
noothness of centerline and radius ve direction, thickness and intensity	(1
ed on observation via $p(\mathbf{z}_t \mathbf{h}_t)$ xp $\{-(d_{\nabla}^2 + \lambda d_{\mu}^2)\}$. (scale to sum to 1)	2
intensity distance over volume of particle V	
² gradient distance over volume of particle V	
com the desired distribution: $\propto p(\mathbf{z}_t \mathbf{h}_t) \sum_{\mathbf{h}_{t-1}} p(\mathbf{h}_t \mathbf{h}_{t-1}) p(\mathbf{h}_{t-1} \mathbf{z}_{1:t-1})$ (1)	3
lean-up	
l until the end are eliminated	
th the scoring function (3)	

• Introduced **particle filter based tracking method** for nerve bundles in high-resolution spine MRI; minimal user input • Defined a **particle representation** for nerve segments & appropriate dynamics model • Described a likelihood measure based on gradient fields and nerve intensities

• Further work: precise estimation of thickness and segmentation of peripheral nerves





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