Spinal Canal Centerline Extraction in MRI

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Abstract

The centerline of the spinal canal holds interesting information which can be used for tasks such as segmenting the spinal canal or to track the progression of spinal deformities. We propose a method that extracts the centerline of the canal by a shortest path search in 4D, whereby dimensions correspond to 3D canal location and canal width. Our method requires only minimal user interaction in the form of two seed points to extract the centerline over the whole length of the spinal canal. We reconstruct the shortest path using a second-order fast marching scheme on a vesselness-based energy. Our approach was evaluated on an MRI dataset of 103 subjects with encouraging results and proved viable with a variety of different parameterizations.

1 Introduction

Diagnosis and treatment of patients suffering from spinal deformities like scoliosis depend heavily on the spinal curvature and its progression over time. Reconstruction of the spinal canal or its centerline is necessary to determine the spinal curvature when using magnetic resonance (MR) images. Once the centerline is known it can be used as a guide or input for other interesting tasks like segmentation of the spinal canal or locating the vertebrae and intervertebral disks.

A lot of work has been done focusing on spinal canal or spinal cord extraction in MR images, as illustrated in Table 1. Some popular approaches include matching a deformable model to the spinal canal surface [3, 4], spinal crawlers [1, 8, 9], finite element models [10], dynamic programming [6] and higher-dimensional embeddings of the problem [5]. However, most of these methods are limited due to being viable only for a short segment of the spinal canal, by providing only locally optimal results, or both. Additionally, several minutes of user interaction or runtime is often required.

This paper, in contrast, introduces a robust, fast and globally optimal way to reconstruct the centerline of the spinal canal from the atlas vertebra (C1), which is the most superior one, to the most inferior one, the os sacrum (OS), using minimal user input. Our approach...

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reconstructs the centerline between user-specified points using a shortest path search in 4D, whereby dimensions correspond to 3D canal location and canal width. A fast marching scheme is used on a vesselness-based energy to find the shortest path. An MR dataset of 103 subjects was used to evaluate our approach. Note that our data set is of low resolution compared to most of the related work.

2 Methods

Based on a given pair $I_{T_1}/I_{T_2}$ of (aligned) $T_1$- and $T_2$-weighted images we first calculate a feature image by weighted combination according to $w_{T_1}I_{T_1} - w_{T_2}I_{T_2}$, which, for a reasonable combination of weights, focuses on the spinal canal while reducing contrasts between other image structures to a minimum (see Figure 1). Taking the feature map as input, we perform four steps. In the first step, Gaussian smoothing filters are applied. The second step consists of computing an energy that can localize the spinal canal. A fast marching scheme is applied on the energy field in the third step based on user-supplied seed points. We then extract the spinal canal centerline from the fast marching distance field between the seeds.

After user input in the form of two or more points inside the spinal canal is given, finding a globally optimal path connecting these input points is the task at hand. As energy measures are generally sensitive to scale, we smooth the input data with $n$ Gaussian kernels linearly spaced between $\sigma_{\min}$ and $\sigma_{\max}$, using separability of the Gaussian kernel and successive filtering to improve the performance. This results in a 4D intensity field $I(x)$, with $x = (x, y, z, s)$. We then want to find the shortest path connecting the user-specified points, that moves close to the spinal canal centerline. For this, we first define the cost for traveling through each voxel of the field, which means finding an energy function facilitating travel along the centerline. Based on this energy, we determine the path connecting the points with the lowest cost.

We have chosen a combination of vesselness and ridge-centrality measures to compose our energy function. The former is useful to differentiate between voxels inside the spinal canal and outside of it, the latter to penalize the distance from the center in terms of higher energy cost. We use the vesselness presented by Li et al. [7], which bases on the three eigenvalues $\lambda_1$, $\lambda_2$, $\lambda_3$ and their corresponding eigenvectors $e_1$, $e_2$, $e_3$ of the spatial Hessian $H_{xyz}(x)$, sorted by their absolute value, so that $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|$. According to [7], if

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Table 1: Comparison of related work. $T_{1+2}$ denotes $T_1$ and $T_2$ being used together. Interaction and runtimes are specified on per-subject basis. Abbreviations: Seq. = sequence, Inter. = interaction time, Sub. = number of subjects, Run. = runtime, Res. = resolution, C = cervical, T = thoracal, L = lumbar, W = whole, uncl. = unclear, h = hour, m = minute, s. = second, MS = mid-sagittal plane.
\[ \text{sign}(\lambda_1) \neq \text{sign}(\lambda_2), \]  
the structure around the voxel is not similar to a vessel at all, neither dark nor bright. In this case, we set the energy to an arbitrary maximum value \( E_{\text{max}} \). In the other case we use  
\[ E_v = (1 + |\lambda_2| (|\lambda_2| - |\lambda_3|) |\lambda_1|^{-1} (1 + \sigma_s)^{-1} \]  
as scale-normalized \textit{vesselness} energy of the voxel, which responds equally to bright and dark vessels. \( E_v \) ranges from 0 to 1 with larger values representing smaller \textit{vesselness}.

For evaluating \textit{ridge-centrality} we use the fact that the gradient of a point on the centerline of a ridge (either dark or bright) is either zero or pointing in a direction parallel to the ridge. So its dot product with the eigenvectors corresponding to the two eigenvalues with largest magnitude has to be zero and we can use  
\[ E_r(x) = (\| e_1 \cdot \sigma_s \nabla_{xyz} I(x) \| + \| e_2 \cdot \sigma_s \nabla_{xyz} I(x) \|) \cdot 10^{-2} \]  
as a scale-normalized measure for the reciprocal \textit{ridge-centrality} of the voxel, adjusted to the range of the \textit{vesselness} energy by multiplying with \( 10^{-2} \). \( E_r \) approaches 0 in the vicinity of the center of the spinal canal and becomes larger in the boundary area. It is small in areas with nearly constant intensity values too and so would not provide a good energy function on its own. The two energy components are combined to  
\[ E(x) = E_c + w_{E_v} E_v(x) + (1 - w_{E_v}) E_r(x) \]  
with \( w_{E_v} \) being the weight factor. \( E_c \) is a small constant value (we used a value of 0.1) representing the minimum energy needed to pass a voxel, which avoids numerical pitfalls with vanishing distance field gradients later on.

We use this energy as the local speed function for a second-order fast marching scheme. The fast marching distance field is initialized with the first user-defined point as the seed region (incorporating all scales). The calculation terminates when the arrival region of the second point is reached (again incorporating all scales). Then, we trace back the streamline from the arrival region descending the gradient of the distance field. Ultimately reaching the seed region, the resulting path follows the centerline of the spinal canal. Afterwards, we use least-squares spline fitting with supporting points evenly distributed along the superior-inferior axis to approximate the obtained path with a \( C^2 \)-continuous curve. Assuming more than two input points along the spinal canal, this process can be conducted in parallel between multiple adjacent pairs of points, dividing the problem into smaller steps and merging the resulting paths afterwards. This may also be used for post-correction purposes.

### 3 Experiments

We benchmarked our approach on MR images of 103 subjects from the \textit{Study of Health in Pomerania} [11], for which we are given ground truth annotation of the centerline and width of the spinal canal, as illustrated in Figure 1. Images were acquired on a Siemens 1.5 Tesla Magnetom Avanto imager. During the standardized acquisition procedure, a volume of \( 501 \times 903 \times 66 \text{ mm}^3 \) was sliced sagittally into 15 slices at a resolution of 449 x 809 pixels, resulting into voxels of \( 1.1 \times 1.1 \times 4.4 \text{ mm}^3 \) in size (see Hegenscheid et al. [2] for further details). For convenience, we resliced the images to isotropic voxels of \( 1.1 \times 1.1 \times 1.1 \text{ mm}^3 \) during preprocessing using cubic spline interpolation. The experiments were conducted using an Intel Xeon X3480 CPU and 8 GB physical memory. To reduce the overall computation time, four subjects were evaluated at the same time in parallel fully utilizing the
Figure 1: From left to right, the images show the ground truth with thickness, energy field with small sigma, distance field with small sigma, the calculated path and the calculated spline. Nine points (seen as red crosses) are used to define a spline for the ground truth centerline. Additionally, a width is set for each point and interpolated between them. The spline is color-coded based on local curvature. To achieve a higher local contrast a modulo operation was applied to the distance values.

eight cores of the CPU and the physical memory. This way, we reduced the runtime from four minutes to about one minute per subject. The empirically determined standard set of parameters consists of an energy weight $w_E$ of 0.9, four Gaussian scales ranging from 0.5 to 7.5 mm, and three user-specified seed points which took less than 15 seconds per case. Weights of $w_E = 0.5$ were used for feature image generation.

The results for the mean absolute distance (MAD) between the ground truth and calculated centerline are 1.7 mm for the lower quartile ($Q_1$), 2.1 mm for the median ($Q_2$) and 2.6 mm for the upper quartile ($Q_3$). The average MAD is 2.2 mm ± 0.7 mm. The maximum absolute distance or Hausdorff distance (HD) is 4.1 mm for $Q_1$, 5.7 mm for $Q_2$ and 7.6 mm for $Q_3$. The average HD is 6 mm ± 2.2 mm. The calculated centerline is completely inside the spinal canal for all 103 subjects. The results for one of the subjects with strong curvature and two input points are shown in Figure 1. We also tested our approach with varying sets of parameters against the ground truth. The results are evaluated based on their HD and rate of failure. We consider a path to be a failure when it breaks out of the spinal canal at some point. The distribution of the HD across the 103 subjects can be used to compare different sets of parameters. In Figure 2 box plots of the HD across all subjects are shown for different sets of parameters. Only one parameter was changed at any given time to visualize the impact of the parameter changes. The leftmost black box plot represents the standard set of parameters.

The number of input points (red box plots) has only a small impact on the quality of the result. Having more input points has generally a positive effect. However, using two points is sufficient in most cases. When using two input points, a single subject resulted in a failure but a satisfying result can be achieved by adding a third input point about half-way between the two. Since our approach uses information provided by the user, we decided to test how inaccurate input would affect the results. We applied offsets (blue box plots) ranging from
1 mm to 10 mm along each image axis of each input point. Just one axis on one point was changed at any given time. An offset of 5.5 mm or less has almost no effect on the quality of the result. The results start to deteriorate significantly once the input point is set very close to the boundary of the spinal canal. Furthermore, variability of user inputs has only very small local impact on the resulting path.

The sum of our two energy functions (Equation 3) performs better than either energy function by itself, as can be seen in the direct comparison of values 0.8 and 1.0 for the energy weight $w_{E_v}$ (green box plots). The 95th percentile for $w_{E_v} = 1$ is far off the chart at 53 mm and the rate of failure is roughly 10%, while for most sets of parameters there are no such failures or at most one. Using a weighted sum of the $T_1$ and $T_2$ image delivers better results than operating on a single $T_1$ or $T_2$ image. We found that as long as the sign of both weights (brown box plots) is the same the results will be acceptable. To evaluate whether adding the size dimension had any impact at all we tested different numbers of Gaussian scales (purple box plots) ranging from two to eight. Increasing the number of Gaussian scales has a positive impact which diminishes very fast, with six and eight scales performing almost equally well. HD is a worst-case measure only used to show stability against parameter modifications. MAD is still significantly better in all of the named cases.

Additionally, we tested the Gaussian scale the computed path is going through against the spinal canal width from the ground truth. Unfortunately, the correlation between the two is often not significant, leaving room for future work. The path usually stays at meaningful scales for the first and last third of the canal. However, along the central part the path is moving through the smallest scales, probably due to the lack of contrast.

## 4 Conclusion

We presented a globally optimal method to extract the centerline of the spinal canal from the atlas vertebra to the os sacrum that is fast and requires only a few seconds of interaction. We
evaluated our approach on 103 subjects yielding results that stayed inside the canal on all but one subject with just two input points specified by the user. In the failure case, adding another point solved the problem. The calculated centerline typically stays within one voxel extent of the ground truth. Our approach proved viable with a variety of different parameters.

5 Acknowledgements

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References


