A Cortex Segmentation Pipeline for Neurosurgical Intervention Planning

Daniela I. Wellein[1], Matthias Pfeifle[2], Martin Althuizes[1], Lars Voitel[1], Dirk Bartz[1]

[1]VCM/ICCAS, Universität Leipzig
[2]Neurochirurgische Klinik, Universitätsklinikum Tübingen
daniela.wellein@iccas.de

Abstract. Cortex segmentation is a prerequisite for 3D neurosurgical intervention planning. The visualization of the cortical surface along with target and risk structures enables conservative access planning and gives context information about the patient-specific anatomy. We present a pipeline for the segmentation of the cortical surface in T1-weighted MR images. To segment the cortex, we combine watershed and level set segmentation. The cortex segmentation pipeline (CSP) is semiautomatic and designed to let the surgeon influence the intermediate data at any stage of the segmentation process. To evaluate the CSP we used the Segmentation Validation Engine (SVE) by Shattuck et al. [1] and compared the results to three different popular methods (BET, BSE and HWA).

1 Introduction

Along with risk and target structures, 3D neurosurgical intervention planning requires a visualization of the cortex. The sulci and gyri of the cortical surface provide anatomical landmarks which give the surgeon a better overview of the patient-specific anatomy. The course of the sulci and their relation to the target structure facilitates access planning along the sulci and therefore minimizes the destruction of healthy cortical tissue. Prerequisite for the visualization is a segmentation of the cortex. A variety of automated segmentation methods exist. Most popular are the brain surface extractor (BSE, [2]), brain extraction tool (BET, [3]) and the hybrid watershed algorithm (HWA, [4]). These methods let the user specify one to three parameters, perform all calculations, and show only the final result. In contrast, our multi-step pipeline allows the inspection (and correction) of all intermediate results. Therefore, the need for a time consuming trial and error process of finding the right parameters is reduced.

2 Materials and Methods

2.1 Pipeline

We integrated the cortical segmentation pipeline (CSP) into our volume data processing and visualization platform VolV [5]. The segmentation algorithms are based on the Insight Segmentation and Registration Toolkit (www.itk.org). CSP consists of three main steps: Preprocessing, watershed, and threshold level set segmentation (Fig. 1). In the preprocessing step, we use anisotropic diffusion filtering [6] to reduce image noise while retaining edges. The next step utilizes the approach of Hahn et al. [7] to coarsely identify brain tissue in the volume datasets. Here, isovalues of the denoised dataset are inverted and serve as input for a watershed transform, leading to a set of basins. In most cases the cortex is included in one basin, which forms the initial brain mask. To close holes in the mask and reduce leaking, morphological operations are applied. Morphological closing is performed with a spherical kernel with radius $r = 2$ and erosion with a spherical kernel with radius $r = 4$.

In the last step, a refined brain mask is computed with threshold level set segmentation. Input data are given by the original volume dataset and the postprocessed initial brain mask from the watershed segmentation. The level set function deforms the initial brain mask according to the propagation term

$$P(x, y, z) = \begin{cases} g(x, y, z) - l, & \text{if } g(x, y, z) < (u - l)/2 + l \\ u - g(x, y, z), & \text{otherwise} \end{cases} \quad (1)$$

with $g(x, y, z)$ being the isovalue of an arbitrary voxel and l and u being the lower and upper threshold. A careful selection of the level set thresholds (2.2), leads to a brain mask without liquor and blood vessels. Postprocessing the brain mask, leaking is reduced using morphological opening (largest connected component).

2.2 Parameter specification

To let the user influence all intermediate results and simultaneously minimize unnecessary user interaction, we give reference values for the segmentation parameters. The first parameters are required for the selection of the watershed preflood height and the flood level. The preflooding parameter p serves to set all isovalues below $v = g_{\min} + p(g_{\max} - g_{\min})$ to v, with $g_{\min}$ and $g_{\max}$ being the minimal and maximal isovalue in the respective volume dataset. The flood level f controls the number of basins in the segmentation result. In the evaluated volume datasets, $p = 0.1$ and $f = 0.35$ lead to one basin enclosing the brain.

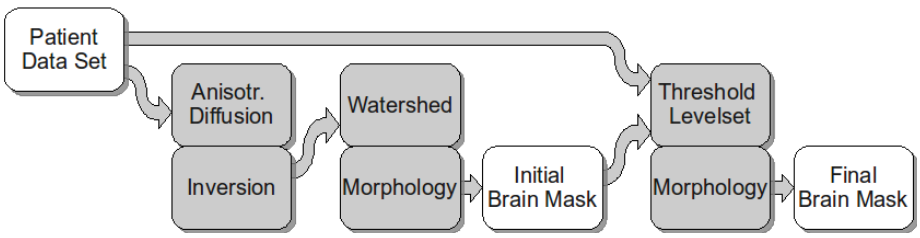

Fig. 1. Workflow of the segmentation pipeline.

Level set thresholds l and u are directly derived from the histogram of the volume dataset. For all cases, three specific points can be identified in the histogram: The local minimum (min), local maximum (max), and the steep slope (slp). In Fig. 2, three histograms with a manually fitted curve and the three points are being showcased. Level set thresholds are chosen, so that $l = \text{min} + (\text{max} - \text{min})/2$ and $u = \text{slp}$.

2.3 Evaluation Methodology

To evaluate the CSP, we applied it to 40 datasets provided in the SVE [1]. SVE compares the segmentation results (S) to a manual cortex segmentation (T) and computes four different quality measures: Sensitivity, Specificity, Jaccard similarity ($|S \cap T|/|S \cup T|$), and the Dice coefficient ($2|S \cap T|/(|T| + |S|)$). Additionally SVE provides error maps of average false positives and negatives and a table of the true positive rates for a variety of different cortical structures.

3 Results

Table 1 shows the results for the CSP compared to three of the most popular cortex segmentation methods. With default parameters, our pipeline achieved an accuracy in the range of the default parameters of BET, BSE and HWA. Mean values with standard deviation are: Jaccard = 0.9239 ($\pm$0.014), Dice = 0.9604

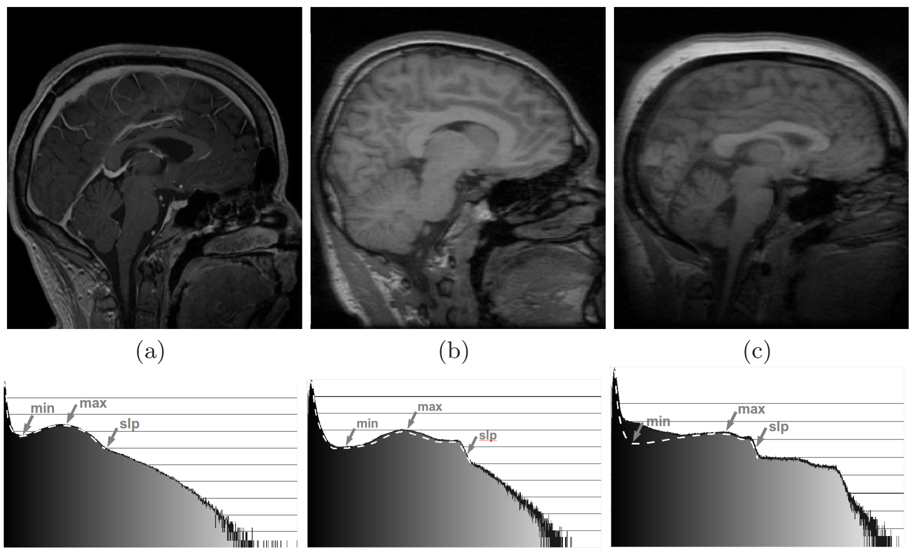

Fig. 2. Example histograms with the min, max and slp marked: (a) with contrast agent, (b) without contrast agent, (c) with signal inhomogeneities. The dashed line marks the course of manually fitted curves.

Table 1. Error metrics for CSP, BET, BSE, and HWA. Reference values from [1] are shown for the default parameters and the best parameters set run.

Method	Parameters	Jaccard	Dice	Sensitivity	Specificity
CSP	default	0.9239	0.9604	0.9543	0.9941
BET	default	0.8919	0.9420	0.9858	0.9804
	-B	0.9400	0.9691	0.9627	0.9957
BSE	default	0.5956	0.7272	0.9804	0.8538
	-n5 -d18 -s0.7 -p	0.9394	0.9684	0.9725	0.9937
HWA	default	0.8531	0.9207	0.9992	0.9693
	-less	0.8537	0.9210	0.9992	0.9695

(±0.008), Sensitivity = 0.9543 (±0.018), and Specificity = 0.9941 (±0.003). The standard deviations indicate that CSP provides satisfactory results throughout all tested volume datasets.

4 Discussion

While Jaccard similarity and Dice coefficient fits in the range of the results of BET, BSE and HWA and specificity is pretty high, sensitivity of the CSP is comparatively low (Tab. 1). This especially occurs for datasets with signal inhomogeneities. As CSP is mainly isovalue based, we cannot deal with large signal

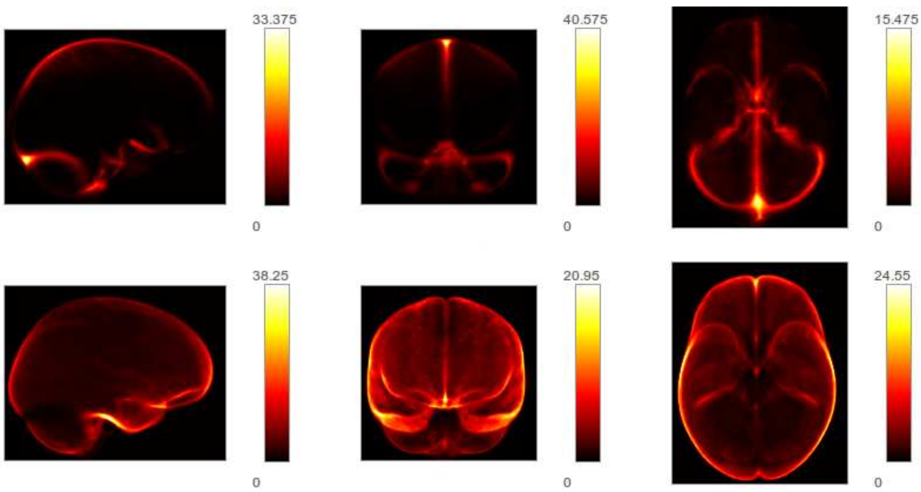

Fig. 3. Error maps for CSP show the average false positives (top) and negatives (bottom). False positives occur at the venous sinus and the eye sockets, false negatives mainly at the temporal lobe.

inhomogeneities. For those datasets and with no inhomogeneity correction our method has to trade leaking for undersegmentation - specificity for sensitivity.

A look at the error maps (Fig. 3) gives a more specific understanding where undersegmentation and leaking occurs. The separation of the venous sinus from the cortex was incomplete and in some cases the segmentation leaks into the eye sockets. Areas with brain tissue missing in the segmentation are located in the temporal lobe.

In the future we aim to reduce the problems of leaking and undersegmentation with an inhomogeneity correction and morphological operations. Also our threshold selection process could be automatized by fitting a curve to the histogram and deriving the *min*, *max*, and *slp* from the fitted curve.

References

1. Shattuck DW, Prasad G, Mirza M, et al. Online resource for validation of brain segmentation methods. NeuroImage. 2009;45(2):431–9.
2. Shattuck DW, Sandor-Leahy SR, Schaper KA, et al. Magnetic resonance image tissue classification using a partial volume model. NeuroImage. 2001;13(5):856–76.
3. Smith SM. Fast robust automated brain extraction. Hum Brain Mapp. 2002;17(3):143–55.
4. Segonne F, Dale AM, Busa BE, et al. A hybrid approach to the skull stripping problem in MRI. NeuroImage. 2004;22:2004.
5. Pfeifle M, Born S, Fischer J, et al. VolV: Eine OpenSource-Plattform für die medizinische Visualisierung. In: Proc CURAC; 2007. p. 193–6.
6. Perona P, Malik J. Scale-Space and edge detection using anisotropic diffusion. IEEE Trans Pattern Anal Mach Intell. 1990;12(7):629–39.
7. Hahn HK, Peitgen HO. The skull stripping problem in MRI solved by a single 3D watershed transform. In: Proc MICCAI; 2000. p. 134–43.