

Min-Cut-Segmentation of WHO Grade IV Gliomas Evaluated Against Manual Segmentation

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Introduction:

Glioblastoma multiforme (GBM)

- one of the highest malignant neoplasms
- evolving from the cerebral supportive cells
- multimodal therapeutical concept involves max. safe resection and is in most cases followed by radiation and chemotherapy
- the survival rate still only accounts approximately 15 months
- for resection and clinical follow-up exact evaluation of tumor-volume is fundamental

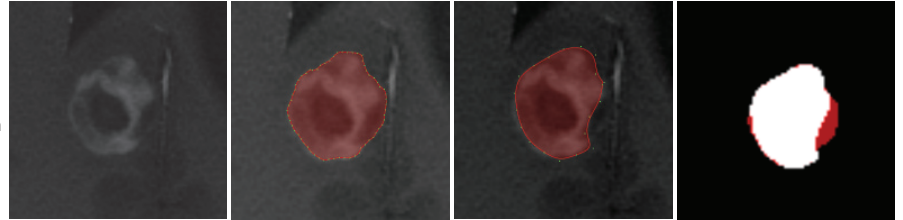


Figure 1: From left to right: Axial slice of a contrast-enhanced T1 weighted MRI scan of a patient with glioblastoma multiforme. Manual segmentation result of a neurosurgeon. Manual segmentation result of the same neurosurgeon two weeks later. Superimposed segmentation results

Methods:

Our GBM segmentation method creates a 3D-graph within two steps:

1. sending rays through the surface points of a polyhedron, with its center located inside the GBM, and
2. sampling the graph's nodes along every ray

Graph construction

- There are two types of ∞ -weighted arcs: z-arcs A_z and r-arcs A_r

$$A_z = \{ \langle V(x, y, z), V(x, y, z-1) \rangle \mid z > 0 \}$$

$$A_r = \{ \langle V(x, y, z), V(x_n, y_n, \max(0, z - \Delta_r)) \rangle \}$$

- Based on the assumption that the user-defined seed point is inside the object, the average grey value can be estimated automatically

$$\int_{-d/2}^{d/2} \int_{-d/2}^{d/2} \int_{-d/2}^{d/2} T(s_x + x, s_y + y, s_z + z) dx dy dz$$

Results:

The presented methods were implemented in C++ within the MeVisLab platform and applied to magnetic resonance imaging (MRI) datasets with GBM

- algorithm's results were evaluated against 12 manual segmentations
- the manual segmentations took on average 8 ± 5.18 minutes (the automatic segmentation took less than 5 seconds for our implementation)
- average Dice Similarity Coefficient (DSC) for all datasets was over 80% (algorithm)
- the DSC for the intra physician segmentation was about 90%

No.	Volume of tumor (cm ³)		Number of voxels		DSC (%)
	manual I	manual II	manual I	manual II	
1	3435.11	2960.56	17076	14717	85.78
2	10871.2	10397.1	54041	51684	93.91
3	2164.53	2076.64	10762	10325	89.82
4	29513.7	28075.3	253521	241165	94.37
5	73452.5	73378.9	78869	78790	95.16
6	43507.7	43630.6	46716	46848	96.3
7	1631.26	1469.92	8109	7307	85.78
8	3226.68	3175.6	16043	15789	89.79
9	9221.88	10325.5	45851	51338	84.97
10	1526	1722	1526	1722	88.79
11	39598.7	38690.2	27240	26615	94.77
12	1488.99	1397.91	14452	13568	84.01

Table 1: Comparison of two manual segmentations of 12 glioblastoma multiforme

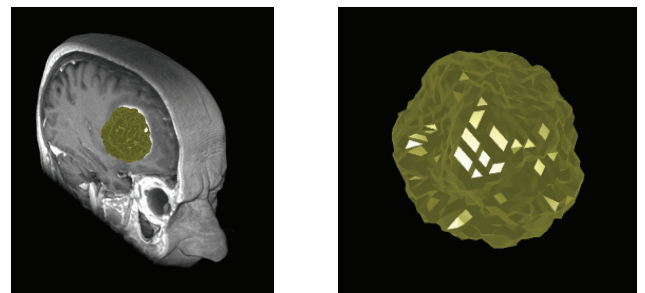


Figure 2: 3D view of an automatically segmented tumor and the voxelized tumor mask

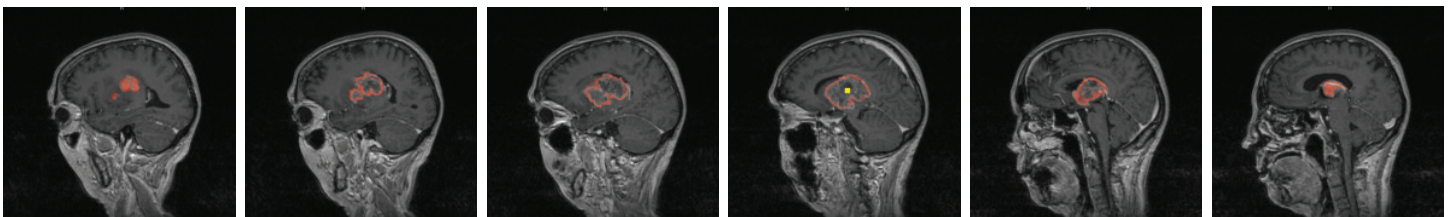


Figure 3: Result of automatic tumor segmentation (DSC=76.19%). The yellow point (inside the tumor) in the fourth image from the left side is the user-defined seed point. Manual segmentation performed by a neurological surgeon took 9 minutes for this data set

Conclusion:

In this contribution, a segmentation method for glioblastoma multiforme (GBM) boundary detection that supports the time-consuming process of volumetric assessment of the tumor was presented and evaluated. Intra physician segmentation demonstrates the reproducibility performing manual boundary extraction and hence provides a quality measure for automatic segmentations. In conclusion, exact and automatic segmentation of brain tumors obtained by our novel approach is useful for planning surgical interventions concerning tumor resection and volumetric assessment in clinical follow-up.

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