Automatic Segmentation of Intraretinal Layers from Optical Coherence Tomography Images

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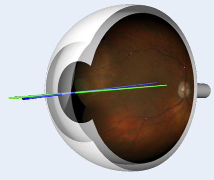
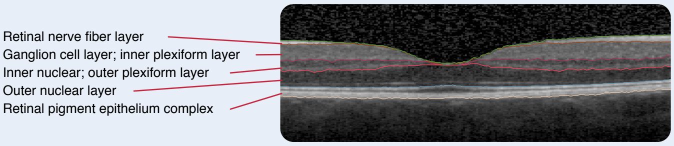


Introduction

Optical Coherence Tomography (OCT) is a non-invasive imaging modality that enables the early detection and also follow-up examination of retinal pathologies. Today's devices produce an enormous amount of imaging data, demanding an automatic assessment of relevant information such as layer boundaries to both support the ophthalmologist detecting and visualizing degenerative changes and also objectively quantify these degenerations. The aim of this work is the development of a segmentation method capable of automatically separating retinal layers (**Figure 1**). The algorithm handles individual slices as well as volumetric images.

Figure 1: Individual segmented retinal layers on an OCT B-scan placed on the fovea.



The improvement over the classical multi-surface segmentation graph-cuts algorithm is the inclusion of true local information.

We extend the classic minimum-closed-set problem (C_{f_i} is the cost of surface f_i) with two new cost terms. The first (C_S) is the cost for a single layer to deviate from an expected shape. The second (C_D) describes the cost of deviating from an expected distance between two layers.

$$C_{\{f_0,f_1,\ldots,f_n\}} = \sum_{i=0}^{n} C_{f_i} + \sum_{i=0}^{n} C_{S_i} + \sum_{i=1}^{n} C_D(f_{i-1}, f_i)$$

Multi-Surface Segmentation

The problem of finding multiple surfaces in the volumetric image is transformed to computing the minimum-closed-set using a minimum s-t cut in a derived arc-weighted directed graph [1]. The nodes in the graph represent image voxels and the resulting cut is the segmentation.

In all figures, directed edges have infinite costs and may never be cut. They are used to compute the minimum-closed-set as well as to incorporate smoothness constraints by limiting the steepness of the surface (**Figure 2**). For simplicity, the graphs in the figures just describe the 2D case.

Segmentation of multiple surfaces is achieved by constructing a graph for each surface and adding connecting edges to constrain the distance between surfaces (**Figure 3**).

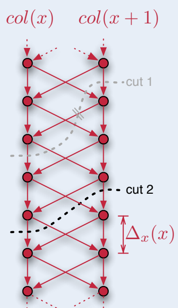


Figure 2: Neighboring nodes may differ in height of max $\Delta_x(x)$. E.g. cut 1 is infeasible, cut 2 is feasible. Since the source is connected to the base of every column, edges may not go from "below" the cut to "above" the cut.

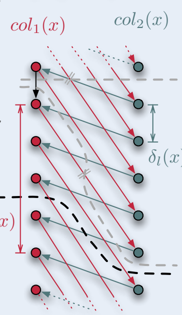
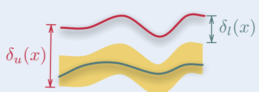


Figure 3: The min $\delta_l(x)$ and max $\delta_u(x)$ distance of the lower surface (green) to the upper surface (red) with example cuts (infeasible grey, feasible black). The resulting possible range for the lower surface is the yellow area in the figure to the left.



Note that a feasible range (yellow area in **Figure 3**) becomes fixed if a single surface (e.g red surface) is already known. By sequentially segmenting the surfaces, we can not only save computation time and memory because we reduce the number of concurrently segmented surfaces, but also because the feasible search range is known, as proposed by [2].

The parameters Δ_x, δ_u, δ_l and the parameters used for the expected surface shape and distances were calculated from the mean shape and variance of a set of manually segmented datasets [2].

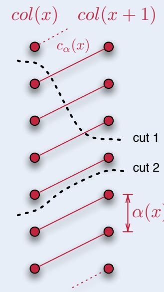
Expected Surface Shape

The expected shape of a single surface can be included in the graph by adding additional undirected edges with cost $c_\alpha(x)$ connecting neighboring columns with the expected height difference $\alpha(x)$ (**Figure 4**).

In this way, if the cut would follow the expected shape, the additional cost would be zero. The cost of any deviation from the expected shape is linear to the amount of the deviation.

$$C_{S_i} = \sum_{x \in I} c_\alpha(x) \cdot |d(x) - \alpha(x)|$$
$$= \sum_{x \in I} c_\alpha(x) \cdot |f_i(x+1) - f_i(x) - \alpha(x)|$$

Figure 4: The cut with the same height difference (cut 2) has 0 additional costs, while cut 1 cuts three edges, thus has cost $3 \cdot c_\alpha(x)$.



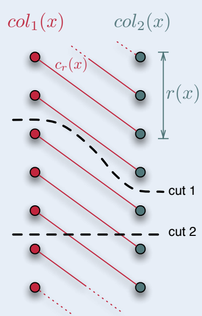
Expected Surface Distance

The expected distance $r(x)$ between two surfaces at an image position x can be incorporated into the graph by adding additional undirected edges. These edges have cost $c_r(x)$ and connect each column $col_1(x)$ (surface 1) with the same column $col_2(x)$ of the surface below (surface 2) (**Figure 5**).

Note that $r(x)$ and $c_r(x)$ are computed for every column position in the image I and include local information.

$$C_D(f_{i-1,f_i} = \sum_{x \in I} c_r(x) \cdot |d_{f_{i-1},f_i}(x) - r(x)|$$
$$= \sum_{x \in I} c_r(x) \cdot |f_i(x) - f_{i-1}(x) - r(x)|$$

Figure 5: The cut through a single column along the expected distance (cut 1) has 0 additional costs from the expected distance constraint, while cut 2 has cost $2 \cdot c_r(x)$.



Results and Outlook

The resulting segmentation works well for healthy retinas. The run time is around 15 seconds for 6 surfaces in a volume of 49 slices per stack and a resolution of 512x496 pixels for each slice.

Because the additional costs for the expected shape serves as a regularization, the resulting segmentation is robust to noise, as well as sparse image information, e.g. missing slices or vessel shadows.

The next step will be an evaluation of the algorithm compared to manual segmentation.

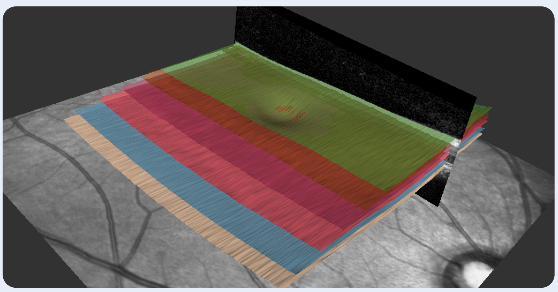


Figure 6: Visualization of the segmented surfaces of an OCT volume scan and with a single slice displayed. The localizer image is shown below the segmented surfaces.

References

1. Li K, Wu X, Chen DZ, Sonka M. Optimal surface segmentation in volumetric images--a graph-theoretic approach. *IEEE transactions on pattern analysis and machine intelligence*. 2006;28(1):119-34.

2. Garvin MK, Abràmoff MD, Wu X, et al. Automated 3-D intraretinal layer segmentation of macular spectral-domain optical coherence tomography images. *IEEE transactions on medical imaging*. 2009;28(9):1436-47.

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