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.

Multi-Surface Segmentation

The problem of finding multiple surfaces in the volumetric image is transformed to computing the minimum-closed-set problem (\(C_F\), is the cost of surface \(f_1\)) 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.

\[
C_{(f_0,f_1,\ldots,f_n)} = \sum_{i=0}^{n} C_{f_i} + \sum_{i=0}^{n} C_{S_{i}} + \sum_{i=1}^{n} C_{D(f_{i-1},f_{i})}
\]

The improvement over the classical multi-surface segmentation graph-cuts algorithm is the inclusion of true local information. We extend the classical minimum-closed-set problem (\(C_F\)) 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.

Expected Surface Shape

The expected shape of a single surface can be included in the graph by adding additional undirected edges with cost \(c_u(x)\) 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.

\[
C_S = \sum_{x \in f} c_u(x) \cdot |d(x) - \alpha(x)|
\]

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 \(c_0(x)\) (surface 1) with the same column \(c_2(x)\) (surface 2) (Figure 5).

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

\[
C_D(f_{i-1},f_i) = \sum_{x \in f} c_r(x) \cdot |f_i(x) - f_{i-1}(x) - r(x)|
\]

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.

References
