Localization of diabetic macular edema areas via graph-based segmentation of OCT retinal images

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Abstract. We propose a technique for localization of diabetic macular edema areas via graph-based segmentation of OCT retinal images. The relevance of the research is associated with the high incidence rate of severe eye conditions due to diabetic macular edema among the world population. The technique relies upon a highly efficient graph-based image segmentation. Using a set of specially selected parameters, the accuracy of retinal area segmentation is enhanced. Optimal parameters found in the course of research have enabled a segmentation error of 2% to be achieved.

1. Introduction
Diabetes mellitus is one of the most common and dangerous endocrine diseases which affects retinal blood vessels, potentially leading to the development of diabetic retinopathy (DR). While all parts of retina get affected by DR condition, changes in its central part in the form of diabetic macular edema lead to the fastest and irreversible vision loss [1]. The accurate and early diagnosis alongside an adequate treatment can prevent vision loss in more than 50% of cases [2-4]. Laser photocoagulation is the 'gold standard' for treatment of DR whose efficiency was confirmed in the course of a major study (ETDRS, 1987) [5].

In the course of laser therapy, a series of dosed microscopic thermal wounds (laser coagulates) are inflicted in the macular edema area. The coagulates are created either sequentially, one by one, or as a specified regular pattern, or according to a preliminary coagulation plan, which is then superposed onto the retina image in real time [6]. Automatic algorithms for creating optimal coagulate maps in the macular edema area [7, 6] require the retinal regions of interest to be localized. Considering the relevance of the problem, the researchers have come up with a number of solutions based on feature generation via discriminative analysis [9, 10], followed by image segmentation [11-13]. A similar segmentation problem is solved when processing satellite images [14-18].

One way to diagnose an eye pathology is through analyzing OCT images (optical coherent tomography) [19], with an OCT image illustrated in Figure 1. In this work, we propose that the OCT images should be utilized to enhance the localization accuracy of the regions of interest previously discussed in the papers [11-13].
To extract the retinal region, segmentation of the original image needs to be conducted, which can be done in a number of ways, including the use of [20].

1) Edge detection algorithms. This technique is hardly applicable to our problem, because the pronounced speckle noise in the original data results in poorly detected discontinuous edges.

2) Clustering algorithms. In addition to being sensitive to the original data quality, this method is also sensitive to the initial parameters, such as the number and initial sets of clusters.

3) Threshold filtering with the use of histograms. The method is ill-suited for our purpose because thresholding is impossible to conduct.

4) A variety of iterative algorithms for region growth. In most cases, the algorithms are too computationally expensive.

5) Methods based on graph cuts. A similar method is proposed in this work.

The initial data are given as a DICOM file composed of a set of OCT images. The method described in this work consists of four stages.

1) Each image is preprocessed in order to remove the vitreous body the image.

2) In each preprocessed image, graph-based segmentation is conducted and the retinal region is extracted.

3) Once all images have been processed, a retina thickness map is built.

4) The map is compared to a reference image and the regions of interest are identified.

2. Preprocessing using an edge detection technique

As we mentioned above, the use of an edge detection algorithm for the original data is of no avail because the OCT images are heavily speckled. This makes accurate edge detection problematic due to frequent swings in the image gradient. However, this technique can still be utilized at the preprocessing stage to reduce the amount of subsequent computations. The essence of this stage is in detecting the retina-vitreous-body boundary.

Known as one of the best-performing edge detectors, Canny algorithm [21] consists of five basic steps:

1) Filter out the noise from the initial image via smoothing. The procedure employs convolution with a Gaussian filter, whose kernel is calculated using the equation (1):

\[
f(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right).
\]  

2) Calculate the intensity gradient and its direction for the smoothed image. The most popular approach consists in the use of the Sobel operator. The angle of the gradient vector is rounded up and quantized to the angles 0°, 45°, 90°, 135°.

3) Apply non-maximum suppression. Only local gradient maximums along specific directions are used for edge detection.
4) Apply double threshold to detect strong and potential edges. If a pixel's value is higher than the high threshold, it takes the maximum value and is marked as a strong edge pixel. If an edge pixel is smaller than the low threshold it is suppressed. A fixed average value is attached to edge pixels found between the high and low thresholds, which are defined more accurately at the next step.

5) Track unambiguous edges. The final edges are detected by suppressing all the edges that are weak and not connected to strong edges. Putting it simply, the problem is reduced to extracting pixel groups that were marked as weak at the previous step and marking them as edge pixels if they are connected to a strong edge or, otherwise, suppressing them. The pixel is included into a group if it is adjacent to this group in one of eight directions.

In our case, applying the Sobel operator in step 2 yields a very rough estimate of the gradient, leading to a fuzzy and discontinuous edge of interest.

As we mentioned above, the noise is filtered out using a Gaussian filter, based on the convolution properties as in equation (2):

$$\frac{d}{dx}(f * H) = f * \frac{d}{dx} H.$$  

Based on equation (2), steps 1 and 2 of the Canny algorithm can be replaced by convolution with a kernel in the form of the Gaussian function derivative.

The image intensity gradient can be derived from equation (3):

$$|G| = \sqrt{G_x^2 + G_y^2}.$$  

The gradient direction angle is given by equation (4):

$$\theta = \arctan \left( \frac{G_x}{G_y} \right).$$

$G_x$ and $G_y$ are directional derivatives relative to $x$ and $y$. Then, considering equations (1) and (2) the filter kernels for calculating the values of $G_x$ and $G_y$ will, respectively, be defined by:

$$f(x,y) = \frac{-x}{2\pi\sigma^2} \exp \left( -\frac{x^2}{2\sigma^2} \right) \exp \left( -\frac{y^2}{2\sigma^2} \right),$$

$$f(x,y) = \frac{-y}{2\pi\sigma^2} \exp \left( -\frac{y^2}{2\sigma^2} \right) \exp \left( -\frac{x^2}{2\sigma^2} \right).$$

The application of the Canny algorithm results in a retina-vitreous-body boundary. At the final step of processing, the region containing the vitreous humor is removed from the image.

3. Efficient graph-based segmentation

The segmentation technique employed is based on a simplified version of an algorithm of efficient graph-based image segmentation [22]. This approach relies on the Kruskal algorithm [23] for constructing a minimum spanning tree of a connected weighted non-oriented graph.

In our case, each pixel is presented as a graph vertex. The graph edges connect neighbor pixels, defined by their weights:

$$w(v_i, v_j) = |I(p_i) - I(p_j)|,$$

where $I(p_i)$ is the value of the intensity function of the pixel $p_i$.

Kruskal algorithm consists of five basic steps:

1) Sort all the edges in the graph in order of increasing weights.
2) Look through the edges in order of increasing weights. Check vertex $v_i, v_j$ of edge $w(v_i, v_j)$.
3) If vertices $v_i, v_j$ belong to the same set, then skip this edge.
4) If vertices $v_i, v_j$ belong to different subsets, then we merge these subsets.
5) We continue the merge cycle to obtain a single set in which all vertices of the graph will be present.

As a result of implementation of the Kruskal algorithm, a set of separate image clusters with minimum summarized edge weights will be formed in the image.

At each step, it is checked whether or not the vertexes of the current minimal-weight edge belong to an already existent cluster. If found to belong to different clusters, the edge weight is compared with the minimal of the maximum-weight edges of the two neighboring clusters. If the current edge has a smaller weight, the clusters get merged.

Denote for cluster \( C_i \) the edge with the largest weight as \( W_{\text{max}}(C_i) \).

For two clusters \( C_i \) and \( C_j \) the current considered edge weight is denoted by \( \text{Edge}(C_i, C_j) \).

Then the merge rule for the two clusters will be defined as equation (7).

\[
\text{Merge}(C_i, C_j) = \begin{cases} 
\text{true, if } \text{Edge}(C_i, C_j) \leq \min(W_{\text{max}}(C_i), W_{\text{max}}(C_j)) \\
\text{false, if } \text{Edge}(C_i, C_j) > \min(W_{\text{max}}(C_i), W_{\text{max}}(C_j))
\end{cases}
\]

(7)

At the final step of algorithm, we check size for each cluster. If size of current cluster below threshold \( M\text{size} \), we merge it with the previous cluster.

Figure 2 depicts the original image and Figure 3 presents results of the segmentation algorithm implementation.

4. Calculating deviations in the retina thickness

After the entire set of OCT images is processed (our study included 85 OCT images for each eye), the retina thickness \( T_e \) can be mapped. Next, comparison with a reference magnitude \( T_n \) is conducted and deviations are calculated using the equation (8).

\[
T_d = \frac{T_e - T_n}{T_n} \cdot 100\%.
\]

(8)

Areas where the deviation estimate is higher than 30% are considered the areas of interest. Using these results, the localization of the regions of interest in the papers [11-13] can be done with a higher accuracy.

5. Results of the experimental study

The experimental study was conducted on 640×940-pixel OCT images. By evaluating various parameters of the algorithms, optimal parameters were empirically chosen.

The parameter \( \sigma \) in equation (5) and equation (6) was chosen based on a criterion of the error of the algorithmically extracted edge relative to the expert-outlined edge. Figure 4 depicts the plot of the error against the parameter \( \sigma \).

For small values of \( \sigma \), the error was large because of numerous edge discontinuities, whereas for \( \sigma \) ranging from 3.5 to 6.5 the error was weakly oscillating around zero. With further growth of \( \sigma \), the
growth of the error was caused by increasingly fuzzy initial data leading to the loss of significant image parameters. The value of $\sigma = 3.5$ was chosen to be optimal.

![Figure 4. Error of edge detection against the parameter $\sigma$.](image)

The image binarization threshold introduced in the Canny algorithm was chosen by a criterion of reduction of spurious edges in the resulting image. Considering that the sought-for edge had the largest value of the intensity gradient a threshold of 0.6 was chosen at which only the line of interest was retained in all images.

An optimal parameter for the percentage of the minimum cluster size was chosen based on two criteria:

1) Reduce the general number of clusters, especially in the region of interest, with the retina being ideally defined by a single segment. However, simultaneously it should be guaranteed that the cluster of interest is not merged with its neighbors. Figure 5 shows a plot for the number of clusters against the percentage of the minimum cluster size. If the parameter is larger than 2.493% the number of clusters decreases slowly.

2) Use the segmentation error of algorithmic region extraction relative to the expert-outlined region. Plotted in Figure 6 is a curve of the error against the percentage of the minimum cluster size.

When the percentage of minimum cluster size was equal to 2.493% a minimum segmentation error of 2% was attained.

This relationship stems from the fact that when the percentage of cluster size is less than 1.662% several clusters simultaneously fit in the region of interest and then the error reduces owing to some pixels migrating between the neighboring clusters. Above the value of 2.493%, the region of interest starts capturing pixels from neighboring clusters, resulting in an increased error.

![Figure 5. A plot of the number of clusters versus the percentage of minimum cluster size relative to the area of the image under segmentation.](image)
Figure 6. A plot of the segmentation error versus the percentage of minimum cluster size relative to the area of the image under segmentation.

6. Conclusion
Summing up, a technique for localization of diabetic macular edema areas via graph-based segmentation of OCT retinal images has been proposed. The relevance of the research is associated with the high incidence rate of severe eye conditions due to diabetic macular edema among the world population. The technique relies upon a highly efficient graph-based image segmentation.

In the course of study, the value of $\sigma=3.5$ was demonstrated to be an optimal value of the $\sigma$ parameter of a filter kernel utilized at a preprocessing stage. The image binarization threshold in the Canny algorithm was chosen based on a criterion of reduction of spurious edges in the resulting image. The best result was attained at a threshold of 0.6. It has been experimentally demonstrated that when the percentage of minimum cluster size equals 2.493% it is possible to attain a retinal segmentation error of 2%.

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