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Automatic Segmentation of Pathological Retinal Layer using Eikonal Equation

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***Abstract*—These Optical coherence tomography (OCT) is a non-invasive diagnostic technique first introduced in 1991. It uses low coherence light waves to render the cross-section view of the retina in micrometer resolution. In the analysis of a retinal anomaly, the sectional visualization proves to be an immensely powerful mechanism. For prior detection of retinal diseases, slicing of the required portion from the dataset images into definite layers is a necessary step. It helps to map and measure their thickness. These measurements help with the diagnosis and provide proper guidance for the treatment of diseases of the retina.**

In this work, we are taking an account of calculating the precise geodesic distance approach for the OCT segmentation of images in two-dimensional spaces. The technique we are using takes into account horizontal and vertical intensity variation and get onto a weighted geodesic distance. By applying the fast marching approach on the Eikonal equation we are calculating the shortest path.

Although the proposed Geodesic distance method using the Eikonal equation is a bit complex method it outperforms graph as well as other techniques in portraying precisely the retinal layers.

***Index Terms*— Retinal Image, Optical Coherence Tomography, Eikonal equation, graph search method, shortest path and fast marching.**

I. INTRODUCTION

Optical coherence tomography (OCT) is an imaging method which does involve any tools that can physically enter the human eye and depends upon low coherence, also known as interferometry. It is a type of optical image modality, which results in high-resolution images of tissue. OCT uses near-infrared light which has a long wavelength to penetrate through the issues. Improvement in methods and algorithms for OCT are under constant improvement in respect of speed and resolution after the introduction in the 1990s. OCT is now becoming a popular imaging technique and used for the detection of diseases. Time delay and magnitude change of low coherence light generate cross-sectional images as analyzed by OCT. A scanned infrared light is divided into two arms the one which falls towards the subject known as sample arm and the other one which falls towards the mirror is known as the alternate arm. When the sample beam reflects back to the instrument the computation of distance change and signal change is done by the photo detector. The change after the obtained result in signal amplitude permits tissue differentiation by examining the reflective

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properties, which matches to a different-color scale. When the scanning beam falls across the tissue, the sequential longitudinal signals which are known as A-scans can be converted into a transverse scan by yielding sectional images which in turn are the B-scans of the retina model. The scans are analyzed by a range of methods giving qualitative morphological information as well as empirical measurements.

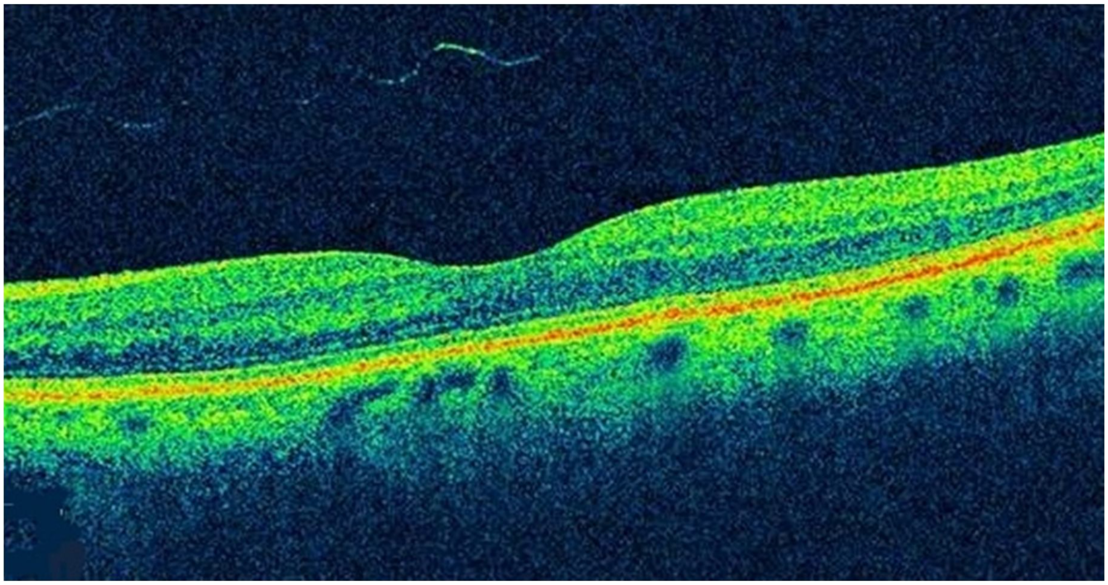

Figure 1: An OCT image from the dataset

The workings of the OCT technique are close to one of the known techniques known as ultrasound, the difference is that ultrasound uses sound wave whereas OCT uses the reflection of light. The resolution orders in OCT are higher than the ultrasound and this is illustrated on both transparent and non-transparent tissue with high reflection. In OCT several A-scans are used at various depths to obtain a two-dimensional image. Those B-scans if observed closely can be converted into a C-scan of a retina.

Time-domain OCT is a technique where depth information of retina is derived after a longitudinal translation in a time of a reference arm. In this half of the light rays from the splitter falls on the mirror at reference arm and the other half scattered and reflected off the tissues structured. The emerging light rays from both arms converge at the beam splitter and then emerge from the other side in the form of an interference pattern that can be sensed by a photo detector. The constructive interference takes place when the distance between light rays directed from tissue structures and reference arm are the same. The interferometer resolution relies on the width of the signal and also inversely proportional to the coherence length of the light.

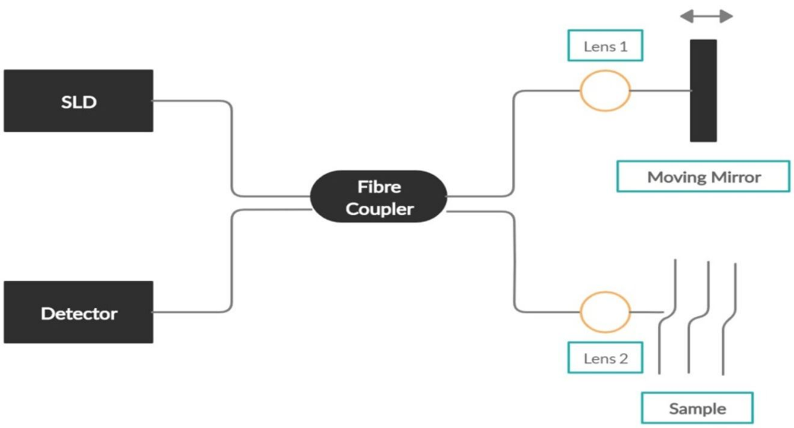

Figure 2: Schematic representation of an TD-OCT System

Spectral Domain OCT (SD-OCT) provides information related to the depth using a spectrometer and advanced mathematics, considering mirror at the constant position. It consists of a spectrometer at the receiver end that scans the spectrum of reflected light that falls on the retina and converts it into the information about the depth of structures which were obtained by using the Fourier principle. The mirror on the reference arm is at a constant position, a grating works similar to a beam splitter which splits the obtained interference pattern into its frequency components. The obtained frequency components are then detected and examined by a charge-coupled device (CCD), that consists of a series of photo detectors. Every photo detector is able to detect the frequency of a specific range. The Fourier transform of the depth of the image is represented by each frequency that is detected and adds it to a resulting A-scan. SD-OCT has allowed near video-rate imaging with shorter addition time. The benefits of these are for real-time eye tracking and calibration of the OCT machine, and various OCT machine vendors have included calibration algorithms in their machines based on tracking.

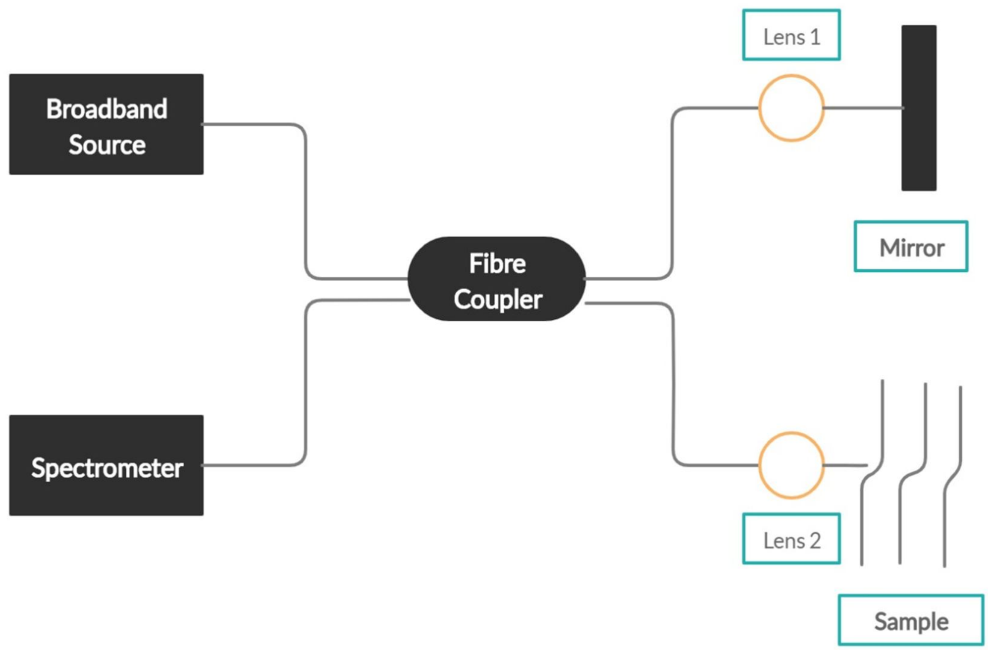

Figure 3: Schematic representation of a SD- OCT System

Within an eye, the different regions are categorized as Vitreous Humor, Retinal Nerve Fiber Layer (RNFL), Ganglion Cell Layer and Inner Plexiform Layer (GCL+IPL), Inner Nuclear Layer (INL), Outer Plexiform Layer (OPL), Outer Nuclear Layer (ONL), Inner Segment (IS), Outer Segment (OS), Retinal Pigment Epithelium (RPE) complex, and Choroid areas.

II. Proposed Method

This section put forth a method for segmenting layered structures. We describe our proposed solution here. Later, we describe the Fast Marching Method (FMM). The following flowchart outlines the core steps in our segmentation algorithm which are discussed below.

A. Pre-processing

Resizing of selected OCT images should be done based on the region of interest. This will save computation time. In the direction of simplifying processing, the resized images were converted into gray scale because in the conversion of this the difference between pixel intensities is enhanced.
In the view of further processing, the speckle noise shows negative effects in processing. So we pre process the images with low pass Gaussian filters to reduce the noise and improve the boundaries.

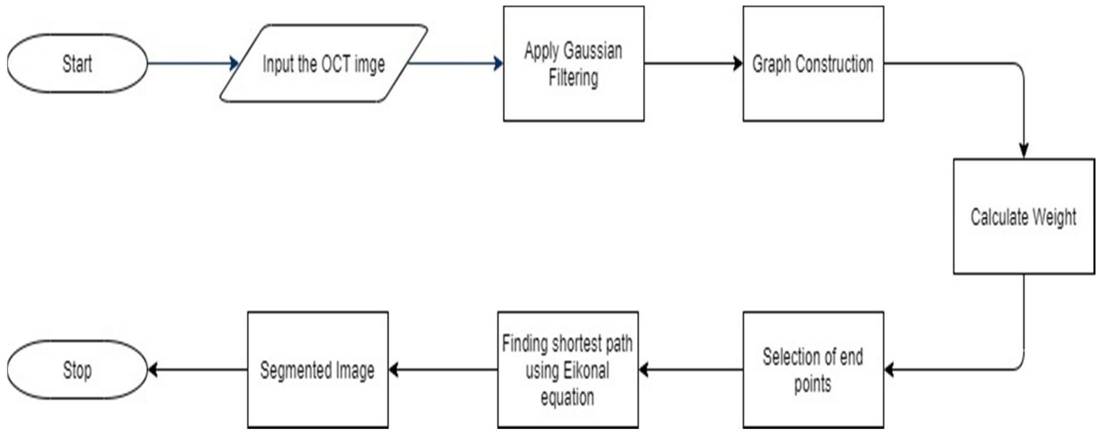

Figure 4: Generalize segmentation algorithm schematic

Graph Representation and weight calculation

We represent each image as a graph G (E, V) where V corresponds to a pixel, and E corresponds to an edge between a pair of nodes. A weight (Wij) assigned from the normalized image gradients i.e (gi and gj). The edge weight (Wij) calculated according to the equation

$$Wij = 2 - (g_i + g_j) + Wmin$$

Wmin is the hypothetical minimum weight.

B. Selection of end points

In order of automated segmentation it is necessary to get a method to initialise endpoints named as s1 and s2 automatically.

Now the shortest path will be calculated using the Eikonal equation. In this regard, it combines both horizontal and vertical gradient data and can then take into account variance in both directions. This will improve the foveal depression areas and highlight weak and low contrast boundaries. As a result, the proposed method can fragment retinal structures with large curvatures. We apply the fast marching method on the Eikonal equation to compute weighted geodesic distance.

James Sethian in the 1990s proposed the fast marching method to unravel boundary related problems generated by the Eikonal equation. It solves the equation on a rectangular mesh in O(N log N), where N symbolizes the total number of grid points. This approach is kind of similar to the Dijkstra's s algorithm that is used for finding the optimal path i.e the shortest distance between points in a graph. It depends on the upwind finite difference and results in a causality relationship that contributes to a Dijkstra like algorithm methodology.

The equation calculates the T(x) (minimum time of arrival question) as shown below:

$$\begin{gathered} |\nabla T(x)| F(x) = 1, \text{on } \Omega \subset \mathbb{R}^N \\ T(x) = 0, x \text{ in } Xs \end{gathered} \quad (1)$$

T(x) means a distance field that contains the time to go from any point x to the closest point in Xs which in turn follows the velocities on F(x). First-order discretization which takes into account the approx derivatives of T(x) via upwind difference method.

$$\begin{gathered} T_x(x) \approx D_{ij}^{\pm x} T = \frac{T_{i\pm1,j,} T_{ij}}{\pm\Delta_x} \\ T_y(x) \approx D_{ij}^{\pm y} T = \frac{T_{i,j\pm1,} T_{ij}}{\pm\Delta_y} \end{gathered} \quad (2)$$

$$\begin{Bmatrix} \max\left(D_{ij}^{-x}T, 0\right)^2 + \min\left(D_{ij}^{+x}T, 0\right)^2 + \\ \max\left(D_{ij}^{-y}T, 0\right)^2 + \min(D_{ij}^{+y}T, 0)^2 \end{Bmatrix} = \frac{1}{F_{ij}^2} \tag{3}$$

$$\begin{Bmatrix} \max\left(D_{ij}^{-x}T, -D_{ij}^{+x}T, 0\right)^2 + \\ \max(D_{ij}^{-y}T, -D_{ij}^{+y}T, 0)^2 \end{Bmatrix} = \frac{1}{F_{ij}^2} \tag{4}$$

Putting Eq. (2) in Eq. (4),

$$\begin{gathered} T = T_{i,j} \\ T_X = \min\left(T_{i-1,j}, T_{i+1,j}\right) \\ T_Y = \min(T_{i,j-1}, T_{i,j+1}) \end{gathered} \tag{5}$$

The equation for a two dimensional space:

$$\max\left(\frac{T-T_X}{\Delta_X}, 0\right)^2 + \max\left(\frac{T-T_y}{\Delta_y}, 0\right)^2 = \frac{1}{F_{ij}^2} \tag{6}$$

$$\left(\frac{T-T_X}{\Delta_X}\right)^2 + \left(\frac{T-T_Y}{\Delta_y}\right)^2 = \frac{1}{F_{ij}^2} \tag{7}$$

The above is a quadratic equation where ;

$$\begin{aligned} a &= \Delta_X^2 + \Delta_Y^2 \\ b &= -2\left(\Delta_y^2 T_X + \Delta_X^2\right) \\ c &= \Delta_y^2 T_X^2 + \Delta_X^2 T_y^2 - \frac{\Delta_x^2 \Delta_y^2}{F_{ij}^2} \end{aligned} \tag{8}$$

Represent Td as the generalization of Tx or Ty for dimension(d), till N dimensions. Also F represent as the propagation velocity. The Eikonal equation discretization is as follows:

$$\begin{aligned} a &= N \\ b &= -2\sum_{d=1}^{N} T_d \\ c &= \left(\sum_{d=1}^{N} T_d^2\right) - \frac{h^2}{F^2} \end{aligned} \tag{9}$$

The Fast marching method is common for solving the Eikonal equation. The fast marching method considered a 'continuous Dijkstra' method. It utilizes a first-order upwind-finite difference scheme to replicate an isotropic front circulation. The variation with Dijkstra's algorithm is that the process is performed on every node. Dijkstra usually works on graphs. Therefore, the value of all node xi depends only on one parent Xj following the Bellman method of optimality:

$$T_i = \min_{X_{i \in N(x_i)}} (c_{ij} + T_j)$$

In other words, node xi is connected to parent xj at its neighboring point N(xi) which reduces the amount of Ti computed by the value of Tj and the addition of the cost of moving from xj to xi, is denoted as cij.

This method follows the Bellman optimality criterion but the value of the universe is calculated by following the first sequence separation of the Eikonal equation. This disclosure takes into account the geographical representation and significance of all causal upwind neighbors. Thus, the arrival times of the land covered by the fastest route are more accurate than those of Dijkstra.

Proposed method tags cells in three different sets: 1) Fixed: In this set all the cells available whose value is already calculated and will not change during a new time, 2) Not_Known: All the cells not having any previously assigned value are categories in this set 3) confined band: cells categories in the Fixed and Not Known set having a value assigned to have the chances of improvement. All three sets mentioned above are different which means a cell cannot be a part of two sets at any certain time.

In the beginning all the points available in the network assigned to Not_Known set having infinite arrival time value. Starting points are classified into Fixed set with a value 0. After that, the loop of Fast Marching Method starts the process with element which is having the lowest arrival time from the Narrow. All the neighbor of non-fixed are assessed. Eikonal will be applied on all of them and the latest time value is assigned only if the value is improved. If the cell belongs to Not_Known then it will be moved to Narrow. At the end the selected locations from Narrow will be moved into Fixed and a fresh loop begins which will end when Narrow set becomes empty. The outcome of this procedure is the arrival time map T which will be returned.

C. The procedure to calculate Fast marching method is as follows :

1. For each neighbor to the starting node(s) compute arrival time. Store it in a sorted list of arrival times.
2. Choose the next unselected node with the shortest arrival time.
3. For each unselected neighbor compute arrival time. Store arrival times in the sorted list of arrival times.
4. Repeat from 2 until all nodes selected.

Algorithm:

```
begin Fast_Marching_Method(X, T , F, Xs)
      Initializing
      Not_Known = X, Narrow = ∅, Fixed = ∅
      Ti = ∞ ∀xi ∈ X
      for xi ∈ Xs do
          Ti = 0
          Not_Known = Not_Known \ {xi}
          Narrow = Narrow ∪ {xi}
   while Narrow is not empty do
       xmin = arg min (xi belongs to Narrow){Ti}
      for xi ∈ (N (xmin) ∩ X \Fixed) do
              Ti = Solve_Eikonal(xi , T , F)
             if Ti < Ti then
                 T1 = Ti
              if xi ∈ Not_Known then
                 Narrow = Narrow ∪ {xi}
                 Not_Known = Not_Known\{xi}
       Narrow = Narrow\{xmin}
       Fixed = Fixed ∪ {xmin}
 return T
end Fast_Marching_Method
```

This proposed method retrieve far better results than the published algorithms for OCT segmentation.

III. RESULT AND ANALYSIS

We compare the results obtained from the proposed method with the results of the segmentation algorithm by graph-cut method. Below table.1 and table.2 shows that the standard deviation and mean of the layers are more accurate for the proposed method by 12 micron and time taken by proposed method is 52 seconds while the graph cut method achieved the layer segmentation in 67 seconds.

TABLE I. COMPARISON CHART FOR STANDARD DEVIATION AND MEAN CALCULATION FOR GRAPH CUT METHOD

'name'	'Mean for Proposed Work'	'sd for Proposed Work'
'ilm - nflgcl'	[25.0243]	[11.2270]
'nflgcl - iplinl'	[26.1083]	[22.7123]
'iplinl - inlopl'	[12.5187]	[11.3948]
'inlopl - oplonl'	[28.2317]	[12.8771]
'oplonl - isos'	[170.2677]	[33.8890]
'isos - rpe'	[42.7357]	[18.0547]

TABLE II. COMPARISON CHART FOR STANDARD DEVIATION AND MEAN VALUE CALCULATION FOR PROPOSED METHOD

'name'	'Mean for Proposed Work'	'sd for Proposed Work'
'ilm - nflgcl'	[21.0143]	[12.3270]
'nflgcl - iplinl'	[20.0083]	[25.6123]
'iplinl - inlopl'	[11.8187]	[11.6948]
'inlopl - oplonl'	[21.8367]	[14.6790]
'oplonl - isos'	[120.7687]	[142.1130]
'isos - rpe'	[52.7557]	[15.1267]

IV. CONCLUSION

The proposed method opt a new technique to solve the shortest path for the retinal layer in an OCT scan images. With the help of eikonal equation fast marching is possible for the real time segmentation process for the medical field. In future, we can opt this method to obtain a more accurate way to apply eikonal equation in retinal OCT scan images with more damage to tissues.

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